VISION BASED OBSTACLE DETECTION IN UAV IMAGING

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ABSTRACT:

Detecting and preventing incidence with obstacles is crucial in UAV navigation and control. Most of the common obstacle detection techniques are currently sensor-based. Small UAVs are not able to carry obstacle detection sensors such as radar; therefore, vision-based methods are considered, which can be divided into stereo-based and mono-based techniques. Mono-based methods are classified into two groups: Foreground-background separation, and brain-inspired methods. Brain-inspired methods are highly efficient in obstacle detection; hence, this research aims to detect obstacles using brain-inspired techniques, which try to enlarge the obstacle by approaching it. A recent research in this field, has concentrated on matching the SIFT points along with, SIFT size-ratio factor and area-ratio of convex hulls in two consecutive frames to detect obstacles. This method is not able to distinguish between near and far obstacles or the obstacles in complex environment, and is sensitive to wrong matched points. In order to solve the above mentioned problems, this research calculates the dist-ratio of matched points. Then, each and every point is investigated for Distinguishing between far and close obstacles. The results demonstrated the high efficiency of the proposed method in complex environments.

1. INTRODUCTION

Nowadays with the increasing usage of UAVs for civil purposes in photogrammetry, agriculture, first-aids, life-saving, etc obstacle detection is a key consideration in UAV navigation.
Obstacle detection becomes more important when UAVs fly in lower altitudes or indoor environment with various obstacles. In those cases, using a UAV with automatic obstacle detection and prevention becomes crucial. Obstacle detection techniques are generally divided into two methods: Sensor-based and vision-based (Zeng, 2016). Sensor-based techniques require sensor data for obstacle detection. Various sensors use laser beams (Shim, 2006), (Shang, 2014), radar (Ariyur, 2005), sonar and ultra-sound (Heidarsson, 2011), (Menezes, 2005). Several factors such as air density can influence sonar and ultra-sonic results (Zeng, 2016). Sonar and ultra-sonic waves are able to measure the position and direction of the obstacle, and their prices are also reasonable, but several factors such as air density can influence their results (Zeng, 2016). Radar waves are proper choices for that purpose in certain cases, particularly when there are not enough or suitable visual data; but radar sensors are usually large, heavy and expensive for using in small UAVs (Huh, 2015). That's why vision-based methods are recommended. These methods are either stereo or mono. Stereo techniques require obtaining the 3D model of the objects; while the mono ones do not need the 3D model. The latter techniques include background and foreground separation methods and brain-inspired methods. Background and foreground separation methods have low efficiency, and detecting obstacles by background and foreground separation is not always a right assumption (Zeng, 2016). Brain-inspired methods use a similar technique based on how human understands and detects obstacles. Various studies have been performed about brain-inspired and mono-based techniques (Mori, 2013), (Al-Kaff, 2016), (Zeng, 2016). One of the key features of obstacle detection algorithms is their functionality in complex environments. As one of the recent techniques, the method proposed by Al-kaff et al. (Al-Kaff, 2016) is to some extent

capable of obtaining obstacle zone in complex environments and is one of the considerable researches in this field. This technique regards an obstacle as an object that is resizing in consecutive frames. At first, SIFT algorithm extracts some key points with their positions (X, Y) and sizes (S) from consecutive frames, and matching is performed between them. Next, the points that are larger in the second frame are compared with those in the previous frame. Then, the sum of size-ratio elements of SIFT in the selected points are regarded as the first criterion, and the area-ratio of the convex hulls of the points is considered to be the second criterion for obstacle detection. Test carried out by us show that this technique is not efficient in distinguishing between close and far obstacles, and regards farther objects as obstacles as well. Figure 1 illustrates the inseparation of far from close objects in Al-Kaff et al's algorithm. Additionally, the presence of wrong matched points will greatly affect the quality of second criterion, i.e. the area ratio of convex hulls. Knowing the above mentioned problems, this research aims to develop Al-Kaff et al's method by presenting a dist-ratio of matched points as an factor to detecting object size changes. This criterion investigates each and every point, so that it can distinguish between far and close points, and can be applied in complex environments. Asides from that, thanks to considering the average dist-ratios in matched points, this criterion will not be influenced by wrong matched points.

Figure 1. Inseparation of far from close obstacles in Al-Kaff et al's algorithm

The rest of this paper is organized as follows. Section 2 is about the research background and section 3 explains methodology, implementation and evaluation. Section 4 demonstrates the conclusions.

2. RESEARCH BACKGROUND

Vision-based obstacle-detection techniques include stereo-based and mono-based. Stereo-based methods are widely used for detecting obstacles (Labayrade, 2012), (Park, 2015). These methods commonly form disparity images and 3D model of the obstacles and objects. These techniques are time-consuming, so they are not suitable for real-time detection (Zeng, 2016). The study of Park et al. (Park, 2015) detects obstacles by obtaining disparity image and contour-map.

Mono-based methods don't need demonstrating the 3D model of the objects and are diverse. These techniques include background and foreground separation methods and brain-inspired methods. In background and foreground separation techniques, the obstacle is regarded as the foreground of the image. Mashaly et al. (Mashaly, 2016) have introduced a technique for distinguishing sky in an image with complex background. Their research processes the data and delivers a binary image, which separates the obstacles from sky. HUH et al's study (Huh, 2015) finds the horizon line for separating sky from ground, detects the movement of moving objects, and applies particle-filter algorithm for detecting moving obstacles. This technique is helpful for moving obstacles, but not applicable for fixed objects. Its other failing is inefficiency for indoor use and low-altitude imaging. On the whole, background and foreground separation methods for object detection are limited to the images in which the separation of obstacle from background is easy. On the other hand, foreground is not necessarily an obstacle. This reduces the functionality of those techniques and, the assumption of obstacle-detection by separating background from foreground is not always correct (Zeng, 2016).

Brain-inspired techniques mimic human's obstacle comprehension techniques. For instance, Mori et al. (Mori, 2013) investigate detecting and preventing the obstacles that move toward or in front of MAV camera. Their study assumes that the objects coming toward camera are subject to change in size and dimensions; hence, It uses SURF algorithm features for detecting obstacle position. Zeng et al. (Zeng, 2016) explains, human eye elements are sensitive to the borders of objects, and the movement of edges or borders of the object indicate object approaching. If the right border of the object moves to the right, the left edge to the left, the bottom edge to bottom, and the top to the top, this suggests enlargement of the object. This method is applicable only when the background is simple, but it is unfunctional when the background is complex.

Al-Kaff et al. (Al-Kaff, 2016) in another study introduced a technique for searching and detecting obstacles, which mimics human's concept of obstacle existence. In Al-Kaff et al. (Al-Kaff, 2016) method, obstacle is the object that is enlarging in consecutive captured frames. This study does not investigate all parts of the frame for obstacle detection, but it selects only the part that is inside 62 degrees field of view for obstacle detection. This selection is because the obstacles detected outside that field never harm UAV. Additionally, since it calculates only part of the frame, calculation time is significantly reduced. In this study, some key-points are extracted with their positions (X, Y) and sizes (S) from the consecutive frames, and they are matched using Brute-Force Algorithm. Then, the matched points with larger sizes in the second frame than the first one are selected. Afterwards, the ratio of size elements of the selected points in the previous step

are calculated, and the sum of ratios is obtained as the first criterion. In the next step, the ratio of convex hull area is regarded as the second factor. Eventually, if those two ratios exceed a certain threshold, all selected points will be associated with the obstacle.

One of the main features of obstacle detection algorithms is their application in complex environments; thus, Al-Kaff et al's method (Al-Kaff, 2016) is to some extent capable of illustrating obstacle zone in complex environments, while Zeng et al's method (Zeng, 2016) and other brain-inspired techniques are not efficient in such cases. That's why Al-Kaff et al's algorithm (Al-Kaff, 2016) has superiority and preference thanks to its application in complex environments, but it has failings as well; since it does not distinguish between close and far obstacles. The main reason of this problem is selecting all the points that represent SIFT resize from the first to the second frame and are larger than the threshold. This causes both far and close objects to be regarded as obstacles. Asides from that, if wrong matched points enter this technique, they easily influence the convex hull and its calculated area; therefore, the second criterion loses its functionality in these conditions. Knowing all those problems, this research aims to develop Al-Kaff et al's (Al-Kaff, 2016) method by presenting a suitable factor for detecting objects resize; so that this criterion investigates each and every point and extracts closer obstacles in complex environments, and distinguishes between farther and closer objects. Apart from that, the criterion should not be influenced by wrong matched points.

3. METHODOLOGY

This research uses obstacle or object enlargement factor when approaching the UAV, and uses dist-ratio of matched points for developing Al-Kaff et al's method (Al-Kaff, 2016). At first, similar to Al-Kaff et al's method, SIFT is used for extracting several points from two consecutive frames, and matching is, then, done by SIFT Algorithm. Next, the dist-ratio in two consecutive frames is calculated using Formula 1; so if we have two sets of matched points, A=[1, 2, 3,…, n] and B=[1, 2, 3,..., n], in two consecutive frames, the distances between a point in the first frame and all other points in the same frame are calculated. The same procedure is done for the matched point of this point in the second frame as well, and the distances with all points are obtained. Afterwards, dist-ratio is calculated with Formula 1.

$$ratio(dist) = \underline{\hspace{2cm}} \qquad (1)$$

where   i , j = matched points
$dist_1$ (i,j) = distance between i and j in the first frame.
$dist_2$(i,j) = distance between i and j in the second frame

This criterion assumes, if the object enlarges in two consecutive frames, the distance between the two matched points in these two frames grows as well; and if we calculate the ratio of those two distances, it will definitely be larger than 1.

According to the criterion, in the first step, the points that are not related to an obstacle are removed. If the dist-ratio of matched points in the second frame to the first frame is less than or equal to 1, the two points of the distance are selected as the points that are probably not an obstacle. Then, the point that has the maximum selection number as non-obstacle is removed and the procedure of removing non-obstacle points is performed until no point has lower dist-ratio than 1 according to the points around it. Next, the remaining points will be the candidates of obstacle-related points.

After removing the non-obstacle points, the remaining points were obstacle candidates, although this obstacle might be in far or close distance. If the obstacle candidates are farther from the camera, they are subject to less distance changes; and conversely, the closer points indicate higher changes. Al-Kaff et al's research did not separate the obstacle points from each other, and all points with positive changes, when the change is higher than the threshold, are detected as obstacles. If the environment is complex, in order to separate the obstacle from a complex background, the current research proposes another criterion, which is able to distinguish between closer obstacles to the camera and far obstacles. In order to determine the obstacle, the average of the dist-ratios for each obstacle candidate point to other points is calculated. Then, the median of all averages will be obtained. If the median is higher than a threshold, the points with higher average than the median are regarded as obstacle-related points. This process extracts the close obstacle points, and does not select the too far obstacles. If both close and far objects were considered to be obstacles simultaneously, the UAV would have to restrict its maneuver in complex environments. Since close obstacles are the most dangerous for UAV, detecting them gets more priority than far objects. In addition, using the average of matched-points dist-ratios and removing the ratios less than or equal to 1, help the selected criterion not to be influenced by wrong matched-points.

3.1 Implementation and Evaluation

In this step in order to implement the research, video images obtained from a Canon camera were used. With the aim to evaluate the method in both indoor and outdoor space, two videos were used as two datasets. Figure 2 shows two consecutive frames selected from the first and second datasets.
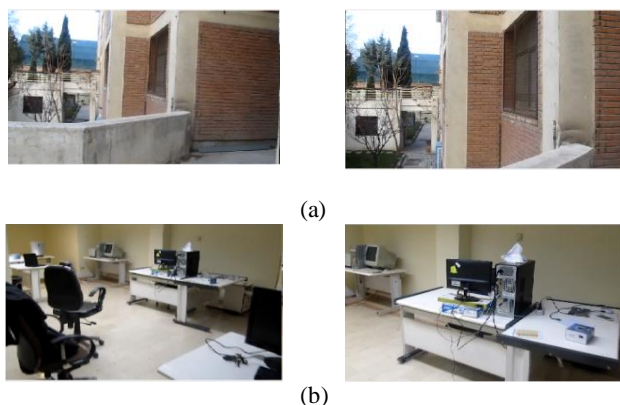

(a)

(b)

Figure 2. a. The first datasets, b. The second datasets

The obtained video was retrieved in Matlab programming environment, and its extracted frames were investigated for obstacle detection. In the next step, SIFT algorithm extracts the matched points of the two frames. The dist-ratio for SIFT is supposed to be 0.40, and 65 and 9 matched points were extracted from the first and second video images respectively. Figure 3a and 4a show the matched points of the first and second videos. Later on, the points with dist-ratio <= 1 were removed as non-obstacle points. Then, 54 and 9 points remained. For the first video, like illustrated in Figure 3b, non-obstacle points are removed and the remaining obstacle candidate points are demonstrated. Most of the matched points that sit in the background in very far distances are eliminated in this step. In the second video, since the extracted points are in closer distance and all points are considered to be obstacles, no point was removed in this step.

Next, the obstacle is obtained by calculating average dist-ratios of each point to other points, and determining the median for those averages; so if the median of two consecutive frames will be higher than 1.1, the points whose average is higher than this median are regarded as obstacle points. 27 and 4 points remain as obstacle points in this phase. As seen in figure 3c and 4c, the closest objects to the camera were selected as obstacles.
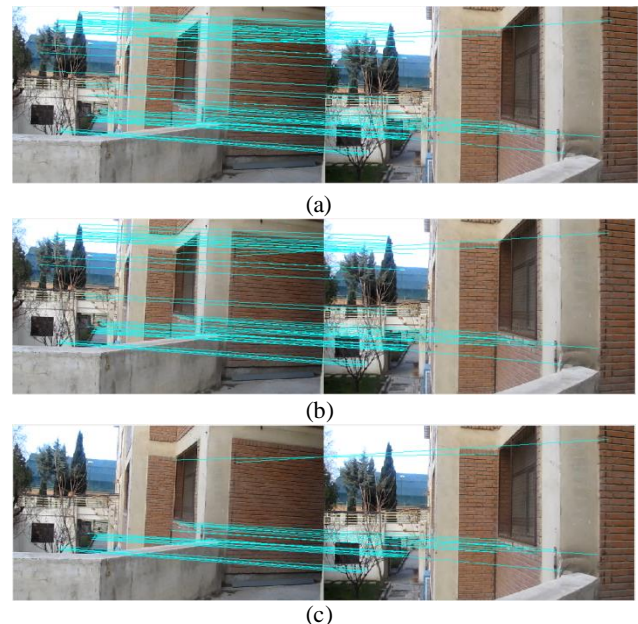

(a)

(b)

(c)

Figure 3. a. Extracted matched points, b. Non-obstacle points are removed and the remaining obstacle candidate points, c. Obtained obstacle points
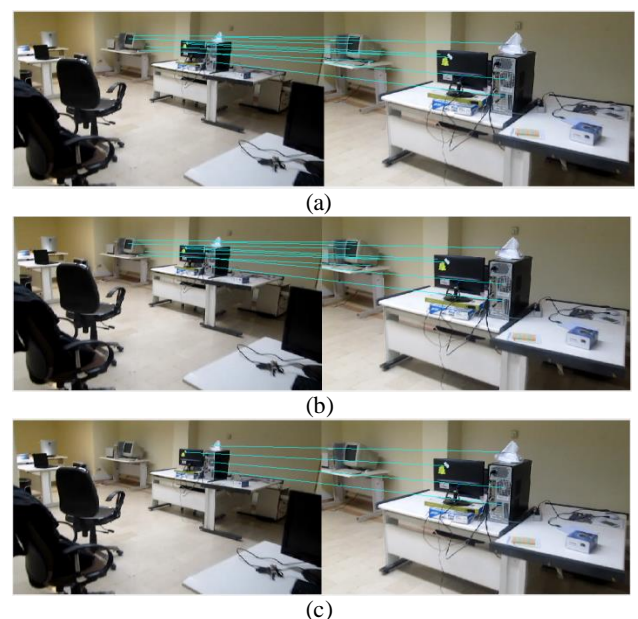

(a)

(b)

(c)

Figure 4. a. Extracted matched points, b. Non-obstacle points are removed and the remaining obstacle candidate points, c. Obtained obstacle points

The current algorithm was compared with al-kaff et al's algorithm. In the beginning, just like the implementation phase, dist-ratio of SIFT was supposed to be equal to 0.4; and the same amount of 65 and 9 points suggested in the previous step were obtained from SIFT Algorithm.

Then, the matched points with higher size parameter than the first frame in the second, are selected as the initial obstacle candidates. The number of remaining points in this step were 54 and 9 points. Afterwards, the convexhulls of the points are illustrated. If the sum of SIFT size-ratios of the matched points obtained from Formula 2 will be greater than 1.2, and the area-ratios of the convexhulls according to Formula 3 will be greater than 1.7, those points will be selected as obstacles.

$$ratio(mkp) = \frac{1}{N}\sum_{i=1}^{N}\frac{Size(mkp_2(i))}{Size(mkp_1(i))} \qquad (2)$$

$$ratio(C) = \frac{Size(C_2)}{Size(C_1)} \qquad (3)$$

where Size ($mkp_1(i)$) = The size of point i in first frame
  Size ($mkp_2(i)$) = The size of point i in second frame
  Size (C1) = The area of convexhull in the first frame
  Size (C2) = The area of convexhull in the second frame

The convex hulls of the points are illustrated. The number of remaining points in this algorithm were 54 and 9 points. Figure 5b & 6b present the results of this algorithm.
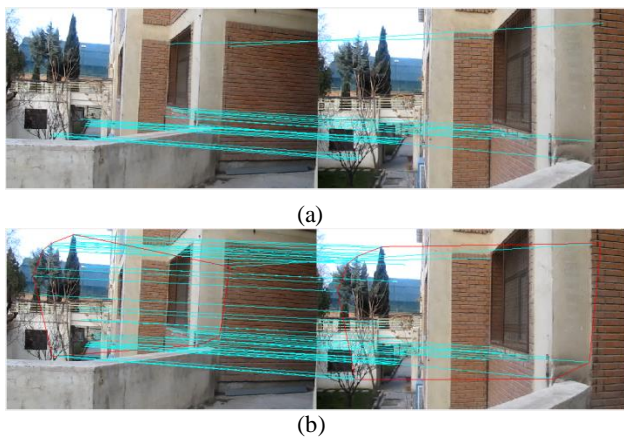

(a)

(b)

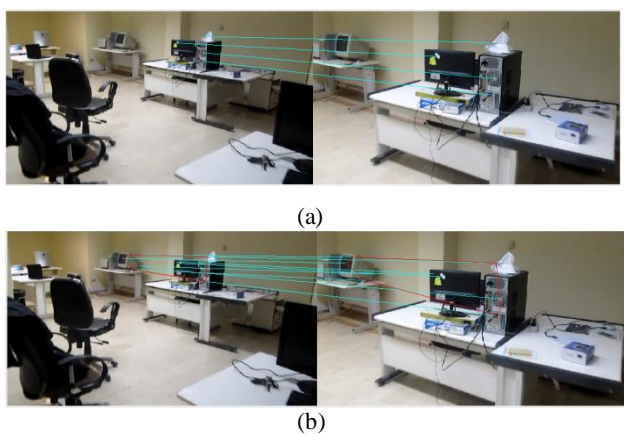Figure 5. a. The result of this research, b. The result of Al- kaff et al.

(a)

(b)

Figure 6: a. The result of this research, b. The result of Al- kaff et al.

As shown in Figure 5 & 6, the Al-Kaff's algorithm does not separate far obstacles from close ones; while the proposed algorithm was able to this properly. The main reason behind this difference is that Al-Kaff et al's algorithm does not investigate and separate each and every obstacle related point, instead it considers all obstacle candidates to be obstacles altogether, if they exceed the threshold; However, our technique appraises each and every point according to the average of their dist-ratios to other points in two consecutive frames.

4. CONCLUSION

The most important function of brain-inspired object detection algorithms are their application in complex environments. As a recent technique, Al-Kaff et al's technique (Al-Kaff, 2016) is able to some extent to detect obstacles in complex environments. However, it cannot separate far obstacles from close ones. Since detecting both far and close obstacles simultaneously restricts the space and reduces UAV maneuverability in complex environments, detecting close objects is the number one priority for UAV navigation. Knowing all that, the current research aims to develop Al-Kaff et al's method (Al-Kaff, 2016) by proposing a suitable criterion for detecting object resize; so that the criterion investigates each and every point and extracts closer obstacles in complex environments, and is also able to separate far from close objects. Moreover, thanks to using the average of matched points dist-ratios and removing ratios <= 1, the selected criterion will not be influenced by wrong matched points.

The results demonstrate the high efficiency of the proposed criterion in detecting obstacles in complex environments.

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