SCIENCE CHINA
Information Sciences

• LETTER •

July 2020, Vol. 63 170208:1–170208:3
https://doi.org/10.1007/s11432-019-2750-y

Special Focus on Bio-Robotic Systems: Modeling, Design, Control and Perception

Vision-based obstacle avoidance for flapping-wing aerial vehicles

Qiang FU[1,2*], Yuhang YANG[1], Xiangyang CHEN[1,2] & Yalin SHANG[1]

[1] *School of Automation and Electrical Engineering, University of Science and Technology Beijing, Beijing* 100083*, China;*
[2] *Institute of Artificial Intelligence, University of Science and Technology Beijing, Beijing* 100083*, China*

Received 29 July 2019/Accepted 29 November 2019/Published online 15 March 2020

Citation Fu Q, Yang Y H, Chen X Y, et al. Vision-based obstacle avoidance for flapping-wing aerial vehicles. Sci China Inf Sci, 2020, 63(7): 170208, https://doi.org/10.1007/s11432-019-2750-y

Dear editor,

The flapping-wing aerial vehicle is a type of bionic robot imitating the flight of birds and insects that generates lift and thrust through the active movement of wings [1]. Its bionic shape has unique advantages in reconnaissance missions [2]. The areas that flapping-wing aerial vehicles need to navigate during their flights may be highly complex and uncertain. Therefore, research into autonomous obstacle avoidance technology for flapping-wing aerial vehicles is essential.

At present, the obstacle avoidance methods commonly used for unmanned aerial vehicles (UAVs) include ultrasonic-, laser-, and vision-based methods. Because of the limitation of ranging ability, ultrasonic-based methods are only suitable for UAVs with slow speeds [3]. Laser-based methods are not suitable for civil UAVs because of their high cost. On the other hand, vision-based methods can provide rich information. In addition, the light weight, small size, and low cost of camera sensors make them very suitable for small UAVs. Binocular (or stereo) cameras can determine the precise distance of obstacles; therefore, they are often used for vision-based obstacle avoidance [4].

In this study, by taking into account the camera parameters and flying speed of a flapping-wing aerial vehicle, we define objects within 6 m of the aerial vehicle as obstacles. To address with the obstacle avoidance problem, an autonomous obstacle avoidance method based on binocular vision is proposed. First, a single-shot multibox detector (SSD) based on deep learning [5] is adopted to detect the obstacles in the image. Then, the distances between the vehicle and the obstacles can be calculated by triangulation and are subsequently used to compute control commands. The experimental results show that the proposed method can accurately provide the distances between the flapping-wing aerial vehicle and obstacles and enables the vehicle to successfully avoid them.

Method. A flapping-wing aerial vehicle usually does not have the ability to hover; therefore, it cannot avoid obstacles in the same manner as multi-rotor UAVs. A flapping-wing aerial vehicle needs to react according to an obstacle's distance. In this study, binocular vision is used to calculate this distance. The binocular vision ranging is achieved first by stereo matching, which uses the left and right images captured simultaneously by the two cameras. Then, the distance of the target object is calculated based on the disparity map obtained by stereo matching. As shown in Figure 1(a), the distance Z of the point P is

$$\frac{B}{Z} = \frac{B-(x_\mathrm{l}-x_\mathrm{r})}{Z-f} \Rightarrow Z = \frac{fB}{x_\mathrm{l}-x_\mathrm{r}}, \qquad (1)$$

where B is the baseline, x_l and x_r are the x coordinates of the image points of P in the left and right images, and f is the focal length of the two identical cameras.

Note that $(x_\mathrm{l}-x_\mathrm{r})$ is defined as the disparity value. To calculate this value, point matches be-

* Corresponding author (email: fuqiang@ustb.edu.cn)

© Science China Press and Springer-Verlag GmbH Germany, part of Springer Nature 2020

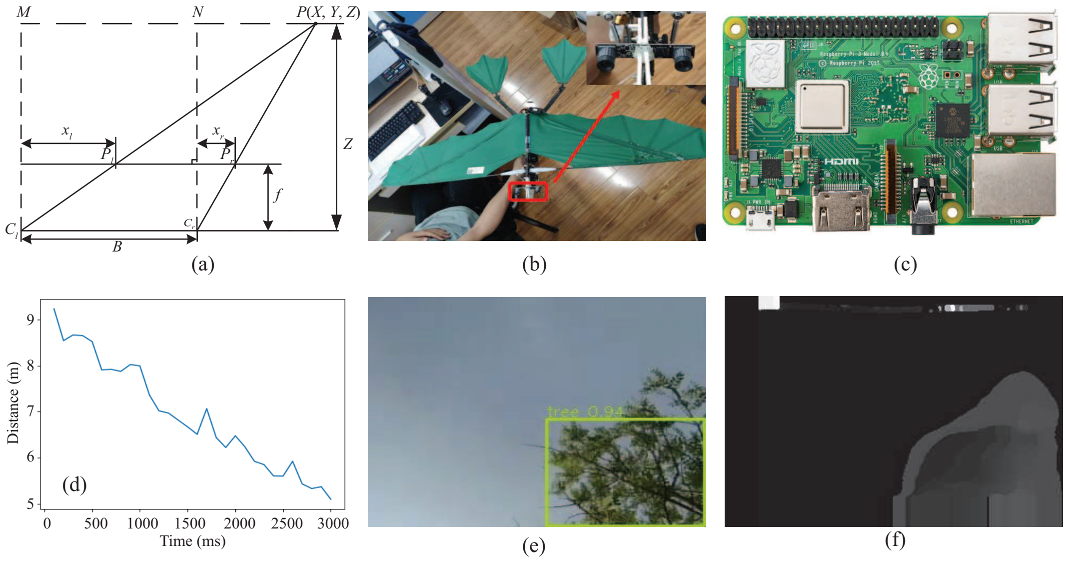

Figure 1 (Color online) (a) Principle of binocular vision; (b) flapping-wing aerial vehicle equipped with the binocular camera system; (c) Raspberry Pi 3b+; (d) the relation between time and distance measured by binocular vision; (e) the result of the SSD algorithm; (f) the disparity map corresponding to (e).

tween the left and right images must be known. The commonly-used block matching algorithm [6] tends to give many mismatches (i.e., outliers), which can cause the disparity map to generate a large number of disconnected areas. Therefore, in this study, the image position of each obstacle is obtained by using an SSD target detection algorithm that considerably reduces the failure to find obstacles owing to mismatches. The SSD target detection algorithm based on MobileNet is first used to obtain the image center of each obstacle, and then the distance between the flapping-wing aerial vehicle and each obstacle is obtained based on (1).

To reduce the computation burden, the original SSD target detection algorithm needs to be modified to make it applicable to our scenario. The trunk network of the SSD target detection algorithm is changed to MobileNet architecture. Using MobileNet architecture greatly reduces the number of parameters and makes the SSD algorithm run considerably faster on the mobile platform [5]. It turns out that after using MobileNet architecture, the memory space of the model is only 34.7 Mb approximately. The model training process for object detection is as follows: First, two hours of video images from aerial photography of the flapping-wing aerial vehicle are collected. Then, one image at every 10 frames is extracted. Note that if the time interval is too small, the similarity of the data set will be very high and an over-fitting phenomenon will occur. Finally, 20000 images are selected and are divided into a training set and a testing set according to a 9:1 ratio [7]. By using labeling software, 10 types of target objects are selected for labeling.

As the distance between the flapping-wing aerial vehicle and an obstacle continues to become smaller, the corresponding control command will be different. Because the precise motion model of the flapping-wing aerial vehicle is difficult to establish, we adopt a simple and easy-to-use PID control method [8]. After many experiments, the steering angle α takes the following form:

$$\alpha = \begin{cases} -k(s-l)^2, & x \leqslant 240 \text{ and } l \leqslant 6, \\ k(s-l)^2, & x > 240 \text{ and } l \leqslant 6, \end{cases} \tag{2}$$

where l is the distance measured by the binocular vision, k is the proportional coefficient, s is the distance threshold for obstacle avoidance, and x is the horizontal image coordinate of the obstacle. Note that s is chosen according to the flight speed of the flapping-wing aerial vehicle and the camera parameters. The parameters of the PID controller are determined by parameter tuning. Based on a large number of experiments, we chose the most suitable parameters as $k = 5$ and $s = 6$.

The steps of the proposed vision-based obstacle avoidance method for flapping-wing aerial vehicles are summarized in Algorithm 1.

Experimental result. In the experiment, a two-tailed flapping-wing aerial vehicle is used, as shown in Figure 1(b). Its total weight is 420 g, and the load weight is 170 g. Two USB cameras with a wide angle of 70° are affixed to the head of the vehicle. The image resolution is 640 × 480 pixels. Target detection algorithms based on deep learning usually rely on powerful computers, such as GPU and TPU, to achieve good results. However, these hardware devices are very heavy and therefore, they cannot be carried by a flapping-wing aerial vehicle. Therefore, we used the most popular card computer, Raspberry Pi 3b+, as our experimental platform [9], which is shown in Figure 1(c). While its size is that of a credit card, it has a 1 GB LPDDR2 SDRAM and weighs only 50 g. At the same time, to ensure the smooth operation of the SSD target detection algorithm, an Intel neural network acceleration bar is used for hardware acceleration.

Algorithm 1 Obstacle avoidance based on binocular vision

Step 1. Give the left and right camera images.

Step 2. Use the SSD target detection algorithm to detect the coordinates (x_1, y_1, x_2, y_2) of the bounding box of the existing target in the left image.

Step 3. Use the block matching algorithm to get the disparity map.

Step 4. Find the smallest distance $l_{\min}$ in a square area with the center point of $(\frac{x_1+x_2}{2}, \frac{y_1+y_2}{2})$ and the side length of 10 pixels.

Step 5. Based on (2), make the flapping-wing aerial vehicle change direction with the horizontal image coordinate $\frac{x_1+x_2}{2}$ if $l_{\min} \leqslant 6$ m.

Step 6. If no target is detected or $l_{\min} > 6$ m, the flapping-wing aerial vehicle does not change direction and continues to fly forward.

When a flapping-wing aerial vehicle flies, the obstacles that it needs to avoid are usually buildings, trees, and so on. The frame rate of Algorithm 1 running on the Raspberry Pi platform is 10 Hz. Because of the low flight speed of the flapping-wing aerial vehicle (approximately 1.5 m/s), the running time basically satisfies the requirement of obstacle avoidance. As can be seen from Figure 1(d), the distance decreases with time. In fact, even when there are trees in front of the vehicle, it does not respond in the beginning because the distance threshold has not been reached. When the distance reduces to 6 m, the vehicle starts changing direction. After a period of time, the obstacle disappears from the field of stereo vision and the distance stops decreasing. Figure 1(e) shows a sample image corresponding to the experiment data in Figure 1(d) from which it is clear that the binocular vision can successfully detect obstacles such as trees. In addition, the disparity map corresponding to Figure 1(e) is given in Figure 1(f) and some white and disconnected areas exist on the top. The reason is probably that outliers still exist in real experiments because of various noises.

Conclusion. In this study, an obstacle avoidance method for flapping-wing aerial vehicles was proposed based on binocular vision. A Raspberry Pi was used as the mobile computing platform. Target detection and stereo matching were combined to improve the accuracy of obstacle detection and binocular ranging. Experimental results showed that the proposed obstacle avoidance method could accurately measure the distance of each obstacle and could successfully avoid it. At the same time, the classification information of the obstacles could be obtained, which may be useful for other applications. In the future, we will further reduce the overall weight of the vision-based obstacle avoidance system, so that it can be applied to small flapping-wing aerial vehicles.

Acknowledgements This work was supported by National Key Research and Development Program of China (Grant No. 2017YFB1300102) and National Natural Science Foundation of China (Grant No. 61803025).

References

1 Mackenzie D. A flapping of wings. Science, 2012, 335: 1430–1433

2 He W, Yan Z, Sun C, et al. Adaptive neural network control of a flapping wing micro aerial vehicle with disturbance observer. IEEE Trans Cybern, 2017, 47: 3452–3465

3 Wen G X, Chen C L P, Dou H, et al. Formation control with obstacle avoidance of second-order multi-agent systems under directed communication topology. Sci China Inf Sci, 2019, 62: 192205

4 Michels J, Saxena A, Ng A Y, et al. High speed obstacle avoidance using monocular vision and reinforcement learning. In: Proceedings of the 22nd International Conference on Machine Learning, Bonn, 2005. 593–600

5 Liu W, Anguelov D, Erhan D, et al. SSD: single shot multibox detector. In: Proceedings of the 14th European Conference on Computer Vision, Amsterdam, 2016. 21–37

6 Zhu S P, Li Z. A stereo matching algorithm using improved gradient and adaptive window. Acta Opt Sin, 2015, 35: 0110003

7 Mazurowski M A, Habas P A, Zurada J M, et al. Training neural network classifiers for medical decision making: the effects of imbalanced datasets on classification performance. Neural Netw, 2008, 21: 427–436

8 He W, Dong Y. Adaptive fuzzy neural network control for a constrained robot using impedance learning. IEEE Trans Neural Netw Learn Syst, 2018, 29: 1174–1186

9 Dorzhigulov A, Bissengaliuly B, Spencer J B F, et al. ANFIS based quadrotor drone altitude control implementation on Raspberry Pi platform. Analog Integr Circ Sig Process, 2018, 95: 435–445