Autonomous quadrotor obstacle avoidance based on dueling double deep recurrent Q-learning with monocular vision

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Abstract

The rapid development of unmanned aerial vehicles (UAV) puts forward a higher requirement for autonomous obstacle avoidance. Due to the limited payload and power supply, small UAVs such as quadrotors usually carry simple sensors and computation units, which makes traditional methods more challenging to implement. In this paper, a novel framework is demonstrated to control a quadrotor flying through crowded environments autonomously with monocular vision. The framework adopts a two-stage architecture, consisting of a sensing module and a decision module. The sensing module is based on an unsupervised deep learning method. And the decision module uses dueling double deep recurrent Q-learning to eliminate the adverse effects of limited observation capacity of an on-board monocular camera. The framework enables the quadrotor to realize autonomous obstacle avoidance without any prior environment information or labeled datasets for training. The trained model shows a high success rate in the simulation and a good generalization ability for transformed scenarios.

Keywords: Unmanned aerial vehicle, obstacle avoidance, deep reinforcement learning

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1. Introduction

Unmanned aerial vehicles (UAV) are widely used in both military and civil fields nowadays. UAVs can liberate people from monotonous or dangerous work scenarios such as searching and rescuing\[1\], package delivery\[2\] etc. However, considering the flight safety, the UAV operation depends on the human remote control or follows a fixed flight route, which may be labor-intensive and inefficient. With the increase of task complexity and scale, it becomes imperative to develop autonomous flight ability. To achieve autonomous flight, the UAV needs to perceive the environment, dealing with the environment information and avoiding obstacles in its expected flight path. Typical on-board sensors for UAV are monocular camera, stereo camera, LIDAR, Kinect\[3\] etc. While some kinds of sensors can output the depth information directly, such as LIDAR and Kinect, others get the depth information with additional calculations like a stereo camera.

The quadrotor is widely used because of its low cost, flexibility and simple structure. Theoretically, quadrotor can utilize sensor data and make proper action decisions to avoid obstacles. Nevertheless, with the restricted payload on it, the weight and energy consumption of equipped sensors are limited. In many cases, quadrotors can only afford to equip a fixed monocular camera, providing limited environment observation only. Therefore, autonomous obstacle avoidance of quadrotor remains a challenging task.

Classical autonomous obstacle avoidance approaches are based on Simultaneous Localization and Mapping (SLAM)\[4, 5, 6\] or Structure from Motion (SfM)\[7\]. Those approaches solve this problem with two separate technological processes, mapping and planning. Firstly they build a local map of surroundings based on sensor data, and then plan a path along with repeatedly updating the local map\[8, 9, 10, 11\]. SLAM and SfM based methods estimate the camera motion and depth by triangulation at each time step. The critical step is the high-frequency feature extraction and matching in the reconstruction of the 3D local map from the sensor data. Though the SLAM and SfM based approaches have been proven to be effective in autonomous obstacle avoidance, their disadvantages are apparent. The feature extraction may fail when facing an untextured obstacle and the real-time process requests unbearable computation for the on-board unit\[12\].

The deep reinforcement learning method provides an alternative to autonomous obstacle avoidance\[13, 14, 15\]. The methods based on deep reinforcement learning does not need feature extraction and matching at the
In this paper, we propose a framework based on the novel deep reinforcement learning algorithm. Our framework applies unsupervised learning based depth estimation method to perceive surrounding obstacles. It makes our framework no longer bothered by the preparation of annotated training data. Since the on-board monocular camera of the quadrotor can only provide a limited field of view, which may lead to the failure of traditional reinforcement learning methods. Our framework is built to make obstacle avoiding decisions according to the previous states rather than only the current one. The trained model shows excellent performance in evaluation, and its performance remains in the transformed scenarios.

The main contributions are as follows:

- We propose a two-stage framework to achieve quadrotor obstacle avoidance with monocular vision. A sensing module and a decision module are connected in series in our framework. The sensing module employs the unsupervised learning approach to perform depth estimation, which takes view synthesis as the supervisory signal. So it can be trained by the raw image sequences captured by the on-board monocular camera. Thus, training the sensing module of our framework is free from the tedious preparing of data with groundtruth.

- We propose a dueling double deep recurrent Q network to learn the obstacle avoidance policy. Since the image acquisition with fixed on-board monocular camera can only provide limited field of view. It leads the quadrotor autonomous obstacles avoidance to become partial observable Markov decision process. Compared to other deep reinforcement models, our proposed network shows better learning efficiency under partial observable conditions.

- We present a feasible solution for obstacle avoidance in scenario transformation. For the new scenarios from the same distribution, the decision module of our framework shows a good generalization. Our decision module can maintain a high success rate when dealing with new
scenarios, even though the appearance, size and location arrangement of obstacles are different from the training scenario.

2. Related work

Learning-based avoidance methods can be divided into end-to-end architecture and hierarchical architecture. The end-to-end architecture goes directly from sensor data to obstacle avoidance actions. Loquercio et al. [18] design a fast 8-layers residual network to output the steering angle and a collision probability for each single input image. The network is trained by the dataset manually annotated by the authors. Kouris et al. [19] train convolutional neural networks (CNN) to predict distance-to-collision from the on-board monocular camera. The proposed CNN is trained on the datasets annotated with real-distance labels, which are obtained by the Ultrasonic and Infra-Red distance sensors. Moreover, Gandhi et al. [17] build a drone to sample data in the crash and their model learns a navigation policy from the sampled dataset. To improve data efficiency, Zhu et al. [20] propose a novel simulation environment to train the model, which provides high-quality 3D scenes and a physics engine. Although the end-to-end models can effectively avoid obstacles, the training of these models needs a large number of data labeled with obstacle distance or collision probability, which requires much manual or special devices annotation. Researchers take efforts to prepare these training data, which costs a lot of time and workforce.

On the other side, many researchers adopt the hierarchical architecture to solve the monocular obstacle avoidance problem. The typical hierarchical architecture contains two separate parts, environment sensing and decision making. The monocular camera can only provide two-dimensional information directly, and it is necessary to perceive three-dimensional information of the environment by utilizing depth estimation. Supervised learning-based depth estimation achieved considerable results [21, 22, 23, 24, 25]. For solving the problem that the labeled datasets are difficult to obtain, researchers have proposed depth estimation methods based on semi-supervised learning [26] and unsupervised/self-supervised learning [27, 28, 29, 30].

Based on various monocular depth estimation methods, researchers have made progress in autonomous obstacle avoidance. Tai et al. [31] build a highly compact network structure which comprises a CNN front-end network for perception and a fully connected network for decision making. The authors record the synchronized depth maps by Kinect and the control commands
by the human operator, and train the network with supervised learning. Sadeghi et al. [32] use the depth channel of Kinect to automatically annotate the RGB images with free-space/non-free-space labels, proposing a learning method to train a fully convolutional neural network, which can be used to perform collision-free indoor flight in the real world. In the paper [33], a fully convolutional neural network is constructed to predict depth from a raw RGB image, followed by a dueling architecture based deep double Q network for obstacle avoidance. Singla et al. [16] use recurrent neural networks with temporal attention to realize UAV obstacle avoidance and autonomous exploration. The authors train a conditional generative adversarial network to generate depth maps from RGB images. For all these researches mentioned above, their model training processes require data with labels or groundtruth. In order to meet the needs of the training process for labeled data, Yang et al. [34] employ an online adaptive CNN for progressively improving depth estimation aided by monocular SLAM, which increases the complexity of the system and the requirements of computation. However, the application scenario of quadrotors is hard to restrict and predict in practice, which increases the difficulty of data acquisition. Therefore, considering the problem of data acquisition, the model training proposed in previous works is neither convenient nor economical, which may limit the practical application of these methods.

In order to reduce the difficulty of training and improve the feasibility of application, we present a novel framework to achieve autonomous obstacle avoidance in this paper. The framework consists of two modules, and its training requires no annotated datasets. The first module is used for sensing the environment, which adopts unsupervised learning based depth estimation to generate a depth map. The second module responds to make obstacle avoidance decisions, whose policy is acquired through deep reinforcement learning. The former one can be trained by raw RGB monocular image sequences, and the latter one can be trained in the simulation environment. In this way, an autonomous obstacle avoidance method is proposed, which is efficient and relatively easy to train. In the face of unknown scenes, our framework only requires raw RGB image data to retrain, and then it can adapt to the new working scenario.
3. Proposed method

In this paper, a two-stage framework is proposed to sense the environment with an on-board monocular camera and make decisions to avoid obstacles in flight. This framework utilizes an unsupervised deep learning method to estimate depth from the raw RGB monocular image. And the framework can further choose proper action to conduct safe flight without collision according to the generated depth information. The selected action acts on the outer loop control of the quadrotor to realize the obstacle avoidance flight. Our framework provides a feasible solution for obstacle avoidance with no prior environment information required.

3.1. Problem definition

The problem of autonomous obstacle avoidance for quadrotor can be reduced to Markov Decision Processes (MDPs), which can be defined as tuple \((\mathcal{S}, \mathcal{A}, T(s_{t+1}|s_t, a_t), R(s_t, a_t))\). Here \(\mathcal{S}\) is the set of states of the environment, while \(\mathcal{A}\) is the set of feasible actions. \(T\) is the transition probability function and \(R\) is the reward function. At each time step \(t\), the vehicle receives the state \(s_t \in \mathcal{S}\) and propose action \(a_t \in \mathcal{A}\). And the received reward \(r_t\) is given by the reward function \(R(s_t, a_t)\). In accordance with the transition model \(T(s_{t+1}|s_t, a_t)\), the vehicle moves into a new state \(s_{t+1}\). The action \(a_t\) is sampled from the policy \(\pi = P(a_t|s_t)\). The expectation of accumulative reward can be approximated by action-state-value function \(Q(s_t, a_t)\), which is constructed by a deep neuron network.

The key to this problem is to find the optimal policy \(\pi\) to maximize the accumulative future reward \(\mathbb{E}\left[\sum_{t}^{\infty} \gamma^t R(s_t, a_t)\right]\), where \(\gamma\) is the discount factor. By choosing the optimal action which maximizes the Q-value each time, the optimal Q-value function can be computed using the Bellman equation

\[
Q^*(s_t, a_t) = \mathbb{E}_{s_{t+1}} \left[ r + \gamma \max_{a_{t+1}} Q^*(s_{t+1}, a_{t+1}) | s_t, a_t \right]
\]

The optimal policy is capable of leading the quadrotor to make correct action decision to avoid obstacles during flight.

In this paper, we simplify the obstacle avoidance problem by fixing the flight altitude and forward speed. And the framework only controls the flight direction by adjusting the yaw angular rate of the quadrotor. The framework uses the image obtained by the monocular camera, which fixed
on the quadrotor at each time step to output the proper flight direction, realizing autonomous navigation without prior obstacle information.

3.2. Sensing with unsupervised depth estimation

The sensing module of our framework constructs a fully connected neural network, which is capable of mapping directly from the input RGB images to the estimate of the underlying scene structure. It employs the DispNet\cite{35} to generate a front view depth map. Inspired by the work in\cite{28}, the network is trained by the supervision signal that the task of novel view synthesis generates. The training process only requires the raw RGB image sequences obtained by the on-board monocular camera while the quadrotor is flying.

The captured image sequences are stored in the replay buffer. The target image and two nearby images in the sequences are sampled from the replay buffer randomly. These images are input to the depth estimation network and pose network at the same time. The depth estimation network generates the depth map $\hat{D}_t$ from the target image. The pose network takes both the target image $I_t$ and the nearby images $I_s$ ($I_{t-1}$ and $I_{t+1}$) in the sequence as input, and outputs the relative camera poses $\hat{T}_{t\rightarrow s}$ ($\hat{T}_{t\rightarrow t-1}$ and $\hat{T}_{t\rightarrow t+1}$). The photometric reconstruction loss between the raw target image and the reconstructed target image is used for training the networks, which can be defined as follows

$$L_{vs} = \sum_s \sum_p |I_t(p) - \hat{I}_s(p)|,$$

where $p$ represents the index over pixel coordinates, the $I_t$ is the raw target image, and $\hat{I}_s$ is the synthesis target image warped from nearby image.

To reconstruct $I_t$, pixels are sampled from $I_s$ based on the depth map $\hat{D}_t$ and the relative pose $\hat{T}_{t\rightarrow s}$. $p_t$ is projected coordinates onto $p_s$ can be obtained as follows

$$p_s \sim K \hat{T}_{t\rightarrow s} \hat{D}_t(p_t) K^{-1} p_t,$$

where $p_t$ represents the coordinates of a pixel in the target view, and $K$ represents the camera intrinsics matrix.

By utilizing view synthesis as supervision, the depth estimation network is trained in an unsupervised manner from captured image sequences. The training pipeline is shown in Figure 1.

3.3. Dueling double deep recurrent Q network

The on-board monocular camera can only provide a limited field of view of the surrounding environment. The partial observability makes it hard to
gain the optimal policy in some particular scenes\cite{16}. As it is shown in Figure 2, the quadrotor might fly straight forward and crash on the obstacle based on the current partial observation, while the proper action is turning left.

Besides, the training data of the depth estimation network is captured by the on-board camera of the quadrotor while it is flying. Unsupervised depth estimation method has been proven feasible, but using on-board camera data to train the model may raise a new problem. The limitation of the quadrotor’s flight ability and the avoidance of crash lead the data to be short of comprehensiveness. And it may cause poor depth estimation performance in some scenes, shown in Figure 3.

Considering the above situations, we treat the quadrotor obstacle avoidance as partially observable Markov decision processes (POMDPs) in this
paper. The POMDP problem can be defined as tuple $\langle S, A, T, R, \Omega, O \rangle$. $S, A, T, R$ are respectively the set of states, actions, transitions, and rewards as before. Here $\Omega$ is the set of observations, while $O$ is the set of probability distributions. The on-board monocular camera gets observations $o \in \Omega$ generated from the underlying system state according to the probability distribution $o \sim O(s)$. At current time $t$, the observation $o_t$ can only represent part of the current surrounding environment state $s_t$. Since estimating Q-value $Q(o_t, a_t|\pi) \neq Q(s_t, a_t|\pi)$, obstacle avoidance action $a_t$ relying entirely on current observation may be fragile. Therefore, in this paper, a method that can use previous observation experience is proposed to make decisions for improving the performance of obstacle avoidance. The model is able to extra useful environment information from sequential observation before the current time, making $Q(o_t, a_t|\pi)$ closer to $Q(s_t, a_t|\pi)$. So it can eliminate the interference of low-quality observation results, and avoid quadrotors getting trapped in cases like the example in Figure 2.

The model is based on the deep recurrent Q network\cite{36} (DRQN) with the dueling and double technology\cite{37, 38}. In the traditional dueling network, two streams are used to compute the value and advantage functions. The dueling network can improve performance and training speed. On the other hand, the double technology solving the problem of overoptimistic value estimation. Based on these previous research results, we combine the DRQN and dueling network by replacing one fully connected layer of the dueling network with an LSTM\cite{39} layer. This dueling deep recurrent Q network structure is shown in Figure 4 and corresponding parameters are shown in Table 1.
Table 1: Parameters of the dueling deep recurrent Q network

| Item            | Size (height,width,channel) | Number | Stride |
|-----------------|----------------------------|--------|--------|
| Depth map       | (128,416,1)                | -      | -      |
| Conv 1          | (8,8,4)                    | -      | 4      |
| Conv 2          | (4,4,8)                    | -      | 2      |
| Conv 3          | (3,3,8)                    | -      | 2      |
| LSTM            | -                          | 1152   | -      |
| FC for advantage| -                          | 5      | -      |
| FC for value    | -                          | 1      | -      |
4. Training and Testing

The model is trained in the Gazebo simulation environment with a step-by-step training strategy. The depth estimation network is firstly trained. Then the trained depth estimation network and the depth maps it generates are used to train the dueling double deep recurrent Q network (D3RQN), which is responsible for performing obstacle avoidance decision making. Several models are trained and evaluated in multiple different simulation environments. Figure 5 shows the screenshots of the basic training environment in simulation.

![Figure 5: The basic training environment in Gazebo](image)

4.1. Depth estimation network

The image collection process is conducted in the simulation environment by the on-board monocular camera of the manually controlled quadrotor. These images are used to train the depth estimation network. The training hyper-parameters are shown in Table 2.

| Parameters               | Value    |
|--------------------------|----------|
| Image number             | 5000     |
| Batch size               | 4        |
| Learning rate            | 0.00005  |
| Image acquisition interval| 0.4s    |
| Camera linear velocity   | 2m/s     |
| Training iteration       | 30000    |

Table 2: Parameters of training the depth estimation network
The depth estimation network is evaluated after training 30000 iterations, which is much less than that in the original paper [28]. The examples of depth estimation are shown in Figure 6. And we test the depth estimation network on an NVIDIA GeForce RTX 2070 GPU with 8 GB RAM and Intel Core i7 processor machine, and the depth map generation rate reaches more than 30Hz.

![Raw images](image1)
![Depth maps](image2)

Figure 6: Examples of depth estimation performance (Red: near, Blue: far)

4.2. Dueling double deep recurrent Q network

The dueling double deep recurrent Q network is also trained in the simulation environment for cost and safety reasons. The network is trained to estimate current Q-value over the last several observations, which means the last several depth maps generated by the depth estimation network. The obstacle avoidance includes five actions, which are defined in Table 3. With each action, the quadrotor obtains a reward which defined as

\[
R = \begin{cases} 
  d_{\text{nearest}} & d_{\text{nearest}} \geq 0.5 \\
  -1 & d_{\text{nearest}} < 0.5 
\end{cases}
\]  

(4)

where the \(d_{\text{nearest}}\) is the distance to the nearest obstacle and the safe distance is 0.5. When the \(d_{\text{nearest}}\) is smaller than the safe distance, the collision is considered to happen and the training episode ends obtaining a negative reward. Besides our dueling double deep recurrent Q network, three other RL based
models are trained in the simulation environment along with similar parameters. They are double deep Q network (DDQN), dueling double deep Q network (D3QN) and double deep recurrent Q network (DDRQN). The learning curves of the four models are shown in Figure 7. Figure 8 presents the comparison of different models. All the data preparing and training processes are on an NVIDIA GeForce RTX2070 machine.

Table 3: Action definition of the quadrotor

| Action num | linear velocity (x,y,z) | angular velocity (x,y,z) |
|------------|-------------------------|--------------------------|
| 1          | (2,0,0)                 | (0,0,0)                  |
| 2          | (2,0,0)                 | (0,0,0.25)               |
| 3          | (2,0,0)                 | (0,0,0.25)               |
| 4          | (2,0,0)                 | (0,0,0.5)                |
| 5          | (2,0,0)                 | (0,0,0.5)                |

Table 4: Parameters of training the dueling double deep recurrent Q network

| Parameters                              | Value |
|-----------------------------------------|-------|
| Batch size                              | 32    |
| Discount factor                         | 0.99  |
| Learning rate                           | 0.0003|
| Input sequence length                   | 5     |
| Action time interval                    | 0.4s  |
| Target network update frequency         | 300   |

The four RL based models are tested in the Gazebo environment. In the test, once the model controls the quadrotor to fly more than 50 steps without collision, we consider it is a success. These models are evaluated by calculating the success rate of each model in 2000 times test flight, the results are shown in Table 5. And in the test, our whole framework can run on the machine mentioned before at more than 15 Hz.

4.3. Performance after scenario transformation

Since the scenario uncertainty in UAV applications is usually strong, the quadrotor obstacle avoidance ability should be effective in different scenarios. Previous researches have focused on building complex models to adapt
Figure 7: Learning curves of the DDQN, D3QN, DDRQN and our D3RQN.

Table 5: Test results of 4 different models

| Model   | Success rate |
|---------|--------------|
| Straight| 0            |
| Random  | 0.002        |
| DDQN    | 0.137        |
| D3QN    | 0.152        |
| DDRQN   | 0.673        |
| Our approach | 0.994        |
Figure 8: The comparison of the four methods after smoothing
to different scenarios as much as possible. However, it is hard for training datasets to cover all possible scenario types. And a complex model is not suitable for the airborne processing unit of a quadrotor. Rather than solving all problems in one model, our approach is dedicated to realizing more convenient training when facing new application scenarios.

In this section, new simulation environments are used to test our model. The appearance, size, shape and location of obstacles in the new simulation environments are different from those in the basic environment in Figure 5. The only thing needed to do before conducting the test is retraining the depth estimation network with image sequences obtained in the new environments. The depth estimation performance after scenario transformation is shown in Figure 9.

![Raw image and Depth map](image)

(a) Raw image  
(b) Depth map

Figure 9: Depth prediction performance after scenario transformation

With the retrained depth estimation network, the whole model is tested in new simulation environments. The screenshots of the test environments are shown in Figure 10. It’s worth emphasizing that we reuse the dueling double deep recurrent Q network trained in the basic environments without any fine-tune operation. These simulation scenarios respectively represent narrow channels, intersections and corners. And Table 6 presents the performance of our method after the scenario transformation.

5. Discussion

In this paper, a deep reinforcement learning based framework is proposed for quadrotor autonomous obstacle avoidance. Our framework has some characteristics as follows:
(a) Env-1: the narrow channel

(b) Env-2: the intersections

(c) Env-3: the corners

Figure 10: The screenshots of the test environments
Table 6: Test results of obstacle avoidance after scenario transformation

| Model      | Success rate |
|------------|--------------|
|            | Env-1 | Env-2 | Env-3 |
| Straight   | 0     | 0     | 0     |
| Random     | 0.003 | 0.001 | 0     |
| Our approach | 0.923 | 0.968 | 0.938 |

- An unsupervised learning-based method for depth estimation is used for the environment perception module in our framework. It is novel to apply this method to the quadrotor autonomous obstacle. In this paper, we train and test the module with raw data obtained by the quadrotor’s on-board monocular camera in the simulation. The training and testing results show that the model can effectively estimate the distance of obstacles on the route of the quadrotor. However, due to the limitation of the quadrotor’s flight ability, the on-board camera is difficult to obtain enough data under certain circumstances, which results in the decline of depth estimation ability.

- The quadrotor mentioned in this paper only relies on a monocular camera to obtain environment information, which limits its observation ability and makes it difficult to make effective obstacle avoidance decisions. To solve this problem, we propose the D3RQN to learn the policy efficiently with limited observations. It can learn the obstacle avoidance policy from previous observations rather than only from the current one. Compared with some other typical RL based methods, our method has better learning efficiency and test performance.

- Since application scenario transformation is pervasive in UAV applications, we tested the performance of the model after transformation. The test results show that our method can effectively make proper obstacle avoidance decisions in the new scenarios after retraining the depth estimation network only, even though the obstacles in new scenarios are different in appearance, shape, size and location arrangement. Besides, retraining the depth estimation network in our framework only requires raw image sequences without labels or groundtruth, which is convenient to prepare.
6. Conclusion

In this paper, the D3RQN framework is presented. It can guide the quadrotor to achieve autonomous obstacle avoidance only by inputting the image captured by an on-board monocular camera. The training and testing results demonstrate that the D3RQN has a better learning efficiency and testing performance than some other approaches such as double DQN, D3QN and double DRQN. The test in different scenarios shows that our framework has good scenario migration ability.

In the future, the framework is going to have a more complex network structure to control the quadrotor with more complex action space. The improvement of training efficiency is also in consideration so that the framework can fit the limited on-board computing resource.

References

[1] S. Waharte, N. Trigoni, Supporting search and rescue operations with uavs, in: 2010 International Conference on Emerging Security Technologies, IEEE, 2010, pp. 142–147.

[2] B. D. Song, K. Park, J. Kim, Persistent uav delivery logistics: Milp formulation and efficient heuristic, Computers & Industrial Engineering 120 (2018) 418–428.

[3] Z. Zhang, Microsoft kinect sensor and its effect, IEEE multimedia 19 (2) (2012) 4–10.

[4] R. Mur-Artal, J. M. M. Montiel, J. D. Tardós, ORB-SLAM: a versatile and accurate monocular SLAM system, IEEE Transactions on Robotics 31 (5) (2015) 1147–1163.

[5] J. Engel, T. Schöps, D. Cremers, Lsd-slam: Large-scale direct monocular slam, in: European conference on computer vision, Springer, 2014, pp. 834–849.

[6] M. Montemerlo, S. Thrun, Simultaneous localization and mapping with unknown data association using fastslam, in: 2003 IEEE International Conference on Robotics and Automation (Cat. No. 03CH37422), Vol. 2, IEEE, 2003, pp. 1985–1991.
[7] C. Wu, Towards linear-time incremental structure from motion, in: 2013 International Conference on 3D Vision-3DV 2013, IEEE, 2013, pp. 127–134.

[8] S. M. LaValle, Rapidly-exploring random trees: A new tool for path planning (1998).

[9] D. Fox, W. Burgard, S. Thrun, The dynamic window approach to collision avoidance, IEEE Robotics & Automation Magazine 4 (1) (1997) 23–33.

[10] Y. Ma, G. Zheng, W. Perruquetti, Z. Qiu, Local path planning for mobile robots based on intermediate objectives, Robotica 33 (4) (2015) 1017–1031.

[11] I. Ulrich, J. Borenstein, Vfh+: Reliable obstacle avoidance for fast mobile robots, in: Proceedings. 1998 IEEE international conference on robotics and automation (Cat. No. 98CH36146), Vol. 2, IEEE, 1998, pp. 1572–1577.

[12] J. Li, Y. Bi, M. Lan, H. Qin, M. Shan, F. Lin, B. M. Chen, Real-time simultaneous localization and mapping for uav: a survey, in: Proc. of International micro air vehicle competition and conference, 2016, pp. 237–242.

[13] D. Silver, J. Schrittwieser, K. Simonyan, I. Antonoglou, A. Huang, A. Guez, T. Hubert, L. Baker, M. Lai, A. Bolton, et al., Mastering the game of go without human knowledge, Nature 550 (7676) (2017) 354–359.

[14] S. Levine, C. Finn, T. Darrell, P. Abbeel, End-to-end training of deep visuomotor policies, The Journal of Machine Learning Research 17 (1) (2016) 1334–1373.

[15] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski, et al., Human-level control through deep reinforcement learning, Nature 518 (7540) (2015) 529–533.

[16] A. Singla, S. Padakandla, S. Bhatnagar, Memory-based deep reinforcement learning for obstacle avoidance in uav with limited environment
knowledge, IEEE Transactions on Intelligent Transportation Systems (2019).

[17] D. Gandhi, L. Pinto, A. Gupta, Learning to fly by crashing, in: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2017, pp. 3948–3955.

[18] A. Loquercio, A. I. Maqueda, C. R. Del-Blanco, D. Scaramuzza, Dronet: Learning to fly by driving, IEEE Robotics and Automation Letters 3 (2) (2018) 1088–1095.

[19] A. Kouris, C.-S. Bouganis, Learning to fly by myself: A self-supervised cnn-based approach for autonomous navigation, in: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2018, pp. 1–9.

[20] Y. Zhu, R. Mottaghi, E. Kolve, J. J. Lim, A. Gupta, L. Fei-Fei, A. Farhadi, Target-driven visual navigation in indoor scenes using deep reinforcement learning, in: 2017 IEEE international conference on robotics and automation (ICRA), IEEE, 2017, pp. 3357–3364.

[21] D. Eigen, C. Puhrsch, R. Fergus, Depth map prediction from a single image using a multi-scale deep network, in: Advances in neural information processing systems, 2014, pp. 2366–2374.

[22] D. Eigen, R. Fergus, Predicting depth, surface normals and semantic labels with a common multi-scale convolutional architecture, in: Proceedings of the IEEE international conference on computer vision, 2015, pp. 2650–2658.

[23] J. Long, E. Shelhamer, T. Darrell, Fully convolutional networks for semantic segmentation, in: Proceedings of the IEEE conference on computer vision and pattern recognition, 2015, pp. 3431–3440.

[24] I. Laina, C. Rupprecht, V. Belagiannis, F. Tombari, N. Navab, Deeper depth prediction with fully convolutional residual networks, in: 2016 Fourth international conference on 3D vision (3DV), IEEE, 2016, pp. 239–248.

[25] Y. Hua, H. Tian, Depth estimation with convolutional conditional random field network, Neurocomputing 214 (2016) 546–554.
[26] Y. Kuznetsov, J. Stuckler, B. Leibe, Semi-supervised deep learning for monocular depth map prediction, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 6647–6655.

[27] C. Godard, O. Mac Aodha, G. J. Brostow, Unsupervised monocular depth estimation with left-right consistency, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 270–279.

[28] T. Zhou, M. Brown, N. Snavely, D. G. Lowe, Unsupervised learning of depth and ego-motion from video, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 1851–1858.

[29] Z. Yin, J. Shi, Geonet: Unsupervised learning of dense depth, optical flow and camera pose, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2018, pp. 1983–1992.

[30] L. Chen, W. Tang, T. R. Wan, N. W. John, Self-supervised monocular image depth learning and confidence estimation, Neurocomputing (2019).

[31] L. Tai, S. Li, M. Liu, A deep-network solution towards model-less obstacle avoidance, in: 2016 IEEE/RSJ international conference on intelligent robots and systems (IROS), IEEE, 2016, pp. 2759–2764.

[32] F. Sadeghi, S. Levine, Cad2rl: Real single-image flight without a single real image, arXiv preprint arXiv:1611.04201 (2016).

[33] L. Xie, S. Wang, A. Markham, N. Trigoni, Towards monocular vision based obstacle avoidance through deep reinforcement learning, arXiv preprint arXiv:1706.09829 (2017).

[34] X. Yang, H. Luo, Y. Wu, Y. Gao, C. Liao, K.-T. Cheng, Reactive obstacle avoidance of monocular quadrotors with online adapted depth prediction network, Neurocomputing 325 (2019) 142–158.

[35] N. Mayer, E. Ilg, P. Hausser, P. Fischer, D. Cremers, A. Dosovitskiy, T. Brox, A large dataset to train convolutional networks for disparity, optical flow, and scene flow estimation, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 4040–4048.
[36] M. Hausknecht, P. Stone, Deep recurrent q-learning for partially observable mdps, in: 2015 AAAI Fall Symposium Series, 2015.

[37] Z. Wang, T. Schaul, M. Hessel, H. Van Hasselt, M. Lanctot, N. De Freitas, Dueling network architectures for deep reinforcement learning, arXiv preprint arXiv:1511.06581 (2015).

[38] H. Van Hasselt, A. Guez, D. Silver, Deep reinforcement learning with double q-learning, in: Thirtieth AAAI conference on artificial intelligence, 2016.

[39] S. Hochreiter, J. Schmidhuber, Long short-term memory, Neural computation 9 (8) (1997) 1735–1780.