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

Jiajun Ou\textsuperscript{a}, Xiao Guo\textsuperscript{a,*}, Ming Zhu\textsuperscript{a}, Wenjie Lou\textsuperscript{b}

\textsuperscript{a}School of Aeronautic Science and Engineering, Beihang University, Beijing 100191, China

\textsuperset{b}School of Electronic and Information Engineering, Beihang University, Beijing 100191, China

Abstract

The fast developing of unmanned aerial vehicle (UAV) brings forward the higher request to the ability of autonomous obstacle avoidance in crowded environment. Small UAVs such as quadrotors usually integrate with simple sensors and computation units because of the limited payload and power supply, which adds difficulties for operating traditional obstacle avoidance method. In this paper, we present a framework to control a quadrotor to fly through crowded environments autonomously. This framework adopts a two-stage architecture, a sensing module based on unsupervised deep learning method and a decision module established on deep reinforcement learning method, which takes the monocular image as inputs and outputs quadrotor actions. And it enables the quadrotor to realize autonomous obstacle avoidance without any prior environment information or labeled datasets. To eliminate the negative effects of limited observation capacity of on-board monocular camera, the decision module uses dueling double deep recurrent Q networks. The trained model shows high success rate as it control a quadrotor to fly through crowded environments in simulation. And it can have good performance after scenario transformed.

Keywords: Unmanned aerial vehicle, obstacle avoidance, deep learning,
1. Introduction

Unmanned aerial vehicles are widely used in both military and civil fields nowadays. UAVs can liberate people from monotonous or dangerous work scenarios like searching and rescuing, package delivery, etc. However, considering the flight safety, the UAV operation depends on human remote control or follows fixed flight route, which may be labor intensive and inefficient. Thus developing the ability of autonomous flight in crowded unfamiliar environment becomes the key to improve the UAV mission efficiency.

To achieve autonomous flight, the UAV needs to sense the environment, deals with the environment information and avoids obstacles in its expected flight path. Typical on-board sensors for UAV are monocular camera, stereo camera, LIDAR, Kinect and etc. While some kinds of sensors can output the depth information directly such as LIDAR and Kinect, others get the depth information with additional calculation like stereo camera. Theoretically the UAV can utilize the sensor data and make proper action decision based on those sensors. But with the restricted payload on small UAV, the weight and energy consumption of equipped sensors are limited. In many cases, small UAV like quadrotors can only afford to equip a fixed monocular camera, which can only provide limited environment observation. The RGB image obtained by monocular camera can only provide two-dimensional environment information directly, while the autonomous obstacle avoidance needs three-dimensional environment information. Therefore, it is necessary to develop depth estimation method to supplement the obstacles distance information. Then the UAV carries out obstacle avoidance based on the supplemented information.

Classical autonomous obstacle avoidance approaches are based on Simultaneous Localization and Mapping (SLAM)\cite{1}\cite{2}\cite{3} or Structure from Motion (SfM)\cite{4}, they 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 repetitively updating the local map\cite{5}\cite{6}\cite{7}\cite{8}. For monocular SLAM and SfM, the camera motion at each time step and corresponding depth estimation follows the triangulation. The critical step is to reconstruct the 3D local map from the sensor data, which typically requires the feature extraction and matching frequently.
Though the SLAM and SfM based approaches have been proven to be effective in autonomous obstacle avoidance, their disadvantages are obvious. The feature extraction may fail when facing untextured obstacle and the real-time process request much computing resource which is unbearable for the UAV onboard compute unit [9].

The present of deep reinforcement learning method provides an alternative to realize autonomous obstacle avoidance [10][11][12]. Because deep reinforcement learning based obstacle avoidance no longer need to perform feature extraction and matching operations, it may be carried out more efficient. In this paper, we put forward a new deep reinforcement learning-based framework. In this framework, the monocular camera image is used to generate depth map by a depth estimation module firstly. Then the depth map is processed into the UAV outer loop control command by the sensor based method. This process is continuously circulated to realize UAV obstacle avoidance in flight. The main contributions are as follows:

- We have proposed a two-stage framework to achieve quadrotor obstacle avoidance with monocular vision, and its training depends on data without groundtruth entirely.
- We have proposed a dueling architecture based deep recurrent Q network which can learn the policy to avoid obstacles efficiently with limited observation.

2. Related Work

Learning based avoidance methods can be divided into end-to-end methods and hierarchical architectures. The end-to-end architecture goes directly from sensor data to obstacle avoidance actions, while the hierarchical architecture usually contains two separate steps, environment sensing and decision making.

Some researches adopt end-to-end learning-based architecture, taking first person view image as input and making decision to avoid obstacles directly. [13] designs a fast 8-layers residual network to output the a steering angle and a collision probability for each single input image. [14] adopts an actor-critic model which obtains the policy from both the goal and current state. [15] trains a CNN to predict distance-to-collision from on-board monocular camera in a self-supervised manner. [16] builds a drone to sample data in crash and learns a navigation policy from the sampled dataset.
Other researches which follow a hierarchical learning-based structure usually use depth estimation approaches in the sensing process. Because the monocular camera can only provide two-dimensional information directly, it is necessary to perceive three-dimensional information of the environment by utilizing depth estimation. Supervised learning based depth estimation method first achieved considerable results [17] [18] [19] [20] [21]. Thereafter, for solving the problem that the labeled datasets are difficult to obtain, researchers have proposed depth estimation methods based on semi-supervised learning [22] and unsupervised or self-supervised learning [23] [24] [25] [26].

Based on various depth estimation methods, researchers have conducted researches to achieve autonomous obstacle avoidance. [27] builds a highly compact network structure to achieve model-less obstacle avoidance which takes raw depth images as input. [28] proposes a learning method which can be used to perform collision-free indoor flight in the real world while being trained entirely on 3D CAD models. [29] proposes a dueling architecture based deep double-Q network for obstacle avoidance, using only monocular RGB vision. [30] uses recurrent neural networks with temporal attention to realize UAV obstacle avoidance and autonomous exploration. [31] employs an online adaptive CNN for progressively improving depth estimation aided by monocular SLAM.

Besides adopting different model architectures, the training of these models mentioned above take different learning approaches. [13] trains the policy by imitating expert behaviour which is generated from wheeled manned vehicles and manually annotated. [16] uses a real drone to collect data while crashing and trains the model with supervised learning. [30] uses labeled datasets to train depth estimation model and learns to avoid obstacles based on it. For all these researches mentioned above, their model training processes require datasets with labels or groundtruth. However, datasets with labels or groundtruth is expensive or even impossible to obtain in practise. Besides, the application scenario of UAV is hard to restrict in practise, which increases the difficulty of data acquisition.

In order to solve the problem of dataset acquisition, we present a framework to achieve autonomous obstacle avoidance in this paper. The training process of our framework depend on data without any label or groundtruth. The framework consists of two parts. The first part is used for sensing the environment, which adopts unsupervised learning based depth estimation to generate depth map. The second part is respond to make obstacle avoidance decision, whose policy is acquired through deep reinforcement learning. The
former part can be trained by raw RGB monocular image sequences and the latter part can be trained in simulation environment. In this way, we propose an autonomous obstacle avoidance method which is efficient and relatively easy to train.

3. Method

In this paper, we propose a two-stage framework to sense the environment with an onboard monocular camera and make decision to avoid obstacles in flight. This framework utilizes the raw RGB monocular image as input, carrying on depth estimation based on unsupervised deep learning method. And the framework can further choose proper action to conduct safe flight without collision according to the generated depth map. 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 sensor-based obstacle avoidance method with no prior environment information required.

3.1. Problem Definition

Autonomous quadrotor obstacle avoidance can be considered as a Markov decision process. Particularly in this paper, the quadrotor interacts with environments with an on-board monocular camera. At current time $t$, the environment state can be defined as $s_t$. The quadrotor chooses an action $a_t$ according to the current state $s_t$. And the quadrotor gets a new position where the surrounding environment state updates to $s_{t+1}$ at the next moment $t+1$. At the same time, the reward $r_t$ is produced according to the action $a_t$ and environment feedback. The key to this problem is finding the optimal policy $\pi$ to maximize the accumulative future reward

$$R_t = \sum_{\tau=t}^{\infty} \gamma^{\tau-t} r_{\tau},$$

where $\gamma$ is the discount factor.

According to the policy $\pi$, the Q-value of each state-action pair $(s_t, a_t)$ can be defined as follows

$$Q^\pi (s_t, a_t) = \mathbb{E} [ R_t | s_t, a_t, \pi ]$$

and by choosing the optimal action which maximizes the Q-value each time, the optimal Q-value function can be computed using the Bellman equation

$$Q^* (s_i, a_i) = \mathbb{E}_{s_{i+1}} \left[ r + \gamma \max_{a_{i+1}} Q^* (s_{i+1}, a_{i+1}) | s_i, a_i \right]$$
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 on-board monocular camera can only provide RGB images with 2D information of the first person view. It is essential to estimate depth to perceive 3D scene information for obstacle avoidance operation. Sensing module in our framework uses the DispNet [32] to generate front view depth map. Inspired by the work in [24], the DispNet 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 are sampled from the replay buffer randomly. These images are input to the depth network and pose network at the same time. The depth 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 $\hat{T}_{t\rightarrow t+1}$). And the photometric reconstruction loss between raw target image and 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 $\hat{I}_s$ based on the depth map $\hat{D}_t$ and the relative pose $\hat{T}_{t\rightarrow s}$. $p_t$’s 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 network is trained in an unsupervised manner from captured image sequences. The training pipeline is shown in Figure 1.

![Figure 1: Unsupervised learning based on view synthesis](image)

### 3.3. Dueling double deep recurrent Q network

Since the onboard monocular camera is fixed on the quadrotor, it can only provide limited vision field of the surrounding environment. The partial observability makes it hard to gain the optimal policy in some particular scenes, 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.

![Figure 2: An example of partial observation which may lead to collision](image)
Besides, the training data of 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 UAV’s flight ability and the avoidance of crash lead the data to be short of quantity, quality and comprehensiveness. And it may cause poor depth estimation performance in some scenes, shown in Figure 3.

![Raw image](image1.png) ![Depth image](image2.png)

Figure 3: Poor performance of depth estimation in some scenes

Considering the above situations, we treat the quadrotor obstacle avoidance as partially observable Markov decision processes in this paper. The on-board monocular camera gets an observation \( o_t \) at current time \( t \). And 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 \( a_t \) which is made relying entirely on current state observations may be fragile. Therefore, in this paper we propose a method that can use previous observation experience to make decisions for improving the performance of obstacle avoidance. The model is able to extra useful environment information from sequential observation before 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[33](DRQN) with the dueling and double technology[34][35]. In the traditional dueling network, two streams are used to compute the value and advantage functions. The dueling network can improve the 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 a LSTM layer. This dueling deep recurrent Q network structure is shown in Figure 4 and corresponding parameters are shown in Table 1.

![Figure 4: The structure of dueling deep recurrent Q network](image)

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 step-by-step training strategy. The depth estimation network is firstly trained by the image data collected from the simulation environment. Then the trained depth estimation network and the depth maps it generates are used to train the dueling double deep recurrent Q network(D3RQN). Several models are trained and tested in multiple different simulation environments. Figure 5 shows the screenshots of the training environment in simulation.
4.1. Depth estimation network

The image collection process is conducted in the simulation environment by the onboard monocular camera of the manually controlled quadrotor. The depth predict network training hyper-parameters are shown in Table 2.

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

The depth estimation network is evaluated after training 30000 iterations, which is much less than in the original paper[24]. The sample of depth prediction is shown in Figure 6. And we test the depth network on a 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, which is sufficient to supply the utilization of obstacle avoidance.

4.2. Dueling double deep recurrent Q network

Considering cost and safety, the dueling double deep recurrent Q network is also trained in the simulation environment. The network is trained to learn the obstacle avoidance policy over the last $P$ observations, which means the
last $P$ depth maps generated by the depth predict network. The obstacle avoidance includes 5 actions which are defined in the Table 3. With each action, the quadrotor obtains a reward which defined as

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

(5)

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 model 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.

The four RL based models are tested in 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. We evaluate these models by computing the success rate of each model in 2000 times test flight, the test results are shown in Table 5. And in the test, our whole framework can run on the machine mentioned before at more than 10 Hz.
### 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                     | 0.4   |
| Target network update frequency          | 300   |

### 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 7: Learning curves of the DDQN, D3QN, DDRQN and our D3RQN.
Figure 8: The comparison of the four methods after smoothing
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 to different scenarios as much as possible. However, it is hard for the training datasets to cover all possible scenario types. And complex model is not suitable for the airborne processing unit of a quadrotor. In this paper, we put forward a new way to solve the problem. Our approach is dedicated to realizing more convenient training when facing new application scenarios, rather than solving all problems in one model.

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

![Figure 9: Depth prediction performance after scenario transformation](image)

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 environments shown in Figure 5 without any fine-tune operation. These simulation scenario respectively represent narrow channels, intersections and corners. And Table 6 presents the performance of our method after scene conversion.
Figure 10: The screenshots of the test environments

(a) Env-1: the narrow channel
(b) Env-2: the intersections
(c) Env-3: the corners
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 |

5. Discussion

In this paper, we propose a deep reinforcement learning based framework for quadrotor autonomous obstacle avoidance. Our framework has some characteristics as follows:

- A unsupervised learning-based method for depth estimation is used for environment perception module in our framework. It is novel to apply this method to quadrotor autonomous obstacle. In this paper, we train and test the module with raw data obtained by the quadrotor’s onboard 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 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 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 observation. It can learn the obstacle avoidance policy from previous observations rather than only from current one. Compared with other RL based methods, our method has better learning efficiency and test performance.

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

- Our model does not require high computing power. After the training, the calculation involved in our framework can be realized on the portable computing device, so our framework has the possibility of running on the actual quadrotor hardware.

6. Conclusion

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

In the future, the framework will have a more complex network structure to control the quadrotor with more complex action space. And the improvement of training efficiency is also in consideration so that the framework can fit the limitation computing resource of the onboard computation unit.

References

[1] 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.

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

[3] 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.
[4] C. Wu, Towards linear-time incremental structure from motion, in: 2013 International Conference on 3D Vision-3DV 2013, IEEE, 2013, pp. 127–134.

[5] S. M. LaValle, Rapidly-exploring random trees: A new tool for path planning.

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

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

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.
[13] 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.

[14] 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.

[15] 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.

[16] 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.

[17] 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.

[18] 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.

[19] 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.

[20] 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.

[21] Y. Hua, H. Tian, Depth estimation with convolutional conditional random field network, Neurocomputing 214 (2016) 546–554.
[22] 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.

[23] 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.

[24] 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.

[25] 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.

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

[27] 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.

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

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

[30] 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.

[31] 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.

[32] 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.

[33] M. Hausknecht, P. Stone, Deep recurrent q-learning for partially observable mdps, in: 2015 AAAI Fall Symposium Series, 2015.

[34] 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.

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

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