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A Vision-Based Robust Adaptive Control for Caging a Flood Area via Multiple UAVs

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Abstract— **This paper presents a control strategy for caging a flood area via multiple UAVs. The strategy consists of the following parts. A novel architecture for video segmentation, Multiscale Features Fusion based MobileNet (MFFM-Net), is constructed to detect the flood boundary. A Function Approximation Technique based Immersion and Invariance (FATII) tracking controller is employed to constrain a single UAV on the flood boundary in the presence of external disturbances. A flocking based formation controller is designed to uniformly distribute UAVs along the flood boundary without collisions among neighbours. The proposed strategy has been verified through simulations under the ROS/Gazebo environment.**

I. Introduction

Large-scale natural disasters occurred worldwide in recent years, among which, flood is one of the most frequent phenomena and leads to a huge economic loss [1]. Therefore, flood management has drawn growing attentions in the field of disaster robotics [2]–[6]. Researches in this field aim to speed up the rescue process for survivors, improve the safety of rescue teams, and prevent secondary disasters.

In the flood management, one of the essential problems is to mark the boundary of a flood area. Traditional methods commonly base on satellites which may lead to high cost and poor real-time performance. In this paper, we provide a UAV-based solution which can detect the flood boundary more efficiently and accurately.

Multiple UAVs are utilized to detect and follow the boundary until the whole flood area is caged. In this caging process, two major issues need to be addressed: one is the vision-based tracking problem, which keeps the boundary of the flood area within the field of vision of each UAV. The other is the formation control problem which aims to evenly distribute UAVs around the flood region without collision.

A. Vision-based adaptive boundary detecting and tracking

The vision-based adaptive boundary tracking problem for a single UAV consists of flood's boundary detecting (through video segmentation) and tracking (through robust adaptive control).

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1) Boundary detecting: Note that to segment a flood area fast and accurately for a mobile robot is challenging as many image segmentation technologies cannot satisfy the hardware requirements of mobile and embedded devices. In 2017, Howard et al. [7] proposed a network model called MobileNet that can be applied to mobile and embedded devices. However, although MobileNet has a good real time performance, the shallow single feature is difficult to be preserved as the deepening of the network, which may lead to a weak accuracy [8], [9]. Multiscale feature fusion technique [10], [11] can improve the video segmentation accuracy by persevering more information from the video, but it has a poor real time performance due to the high computational cost accompanied with the increasing information. To balance the accuracy and the real-time performance, we propose a new architecture for the video segmentation, the MFFM-Net, by combining the advantages of both the MobileNet and the Multiscale Features Fusion technology.

2) Boundary tracking: After the boundary of a flood area is detected, the UAVs need to be constrained on the boundary. To drive the UAVs to the desired positions in the presence of the external disturbances, such as strong wind, in this paper, we design a robust adaptive controller for the UAVs through the Function Approximation Technique based Immersion and Invariance (FATII) method. The proposed FATII based controller is model-free and thus, is applicable to a wide range of systems. Also, it can reject the effect of the system uncertainties or external disturbances to the control system. The asymptotic stability of the FATII controller is established, and its validity is shown by simulations.

B. Formation control

During a flood disaster, a single UAV is difficult to complete the caging task efficiently due to its limited view. Therefore, a formation control algorithm is proposed in this paper for multiple UAVs such that they can cooperate to evenly distribute around the flood area without collisions among each other.

To achieve the desired formation of a multi-agent system, position-based methods [12]–[15] have been proposed to track the position of each agent without any interactions among the agents. However, these methods only work under ideal conditions when absolute positions of all the UAVs can be obtained. Different from the position based methods, the distance-based formation control methods [16]–[19] keep desired distances among neighboring agents to achieve a desired formation of the whole system. However, these methods are not feasible for our caging problem because the

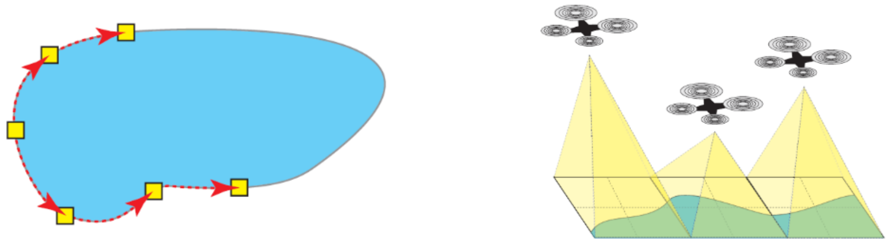

Fig. 1. Illustration of caging a flood area by multiple UAVs.

size of the flood area is uncertain, and therefore, the desired distances between the UAVs are unknown in advance. In this paper, we propose a formation controller through a flocking based method [20]–[24], which automatically adjusts the distances between adjacent UAVs.

The rest of the paper is organized as follows. In Section II we state the research problem. In Section III, we develop a control strategy, implement it by corresponding control algorithms, and verify it under simulation in Section IV. Finally, conclusions are drawn in Section V.

II. Formalization of the Control Problem

The aim of this research is to cage a flood zone by using multiple UAVs (see Fig. 1). Assume that a high-resolution image from a bird's-eye view can be generated from the camera of the UAV. The view is limited such that a single UAV can only see a portion of the flood area. During the caging process, a groups of UAVs are required to detect the whole boundary of the flood area, as shown in Fig. 1, which are represented by yellow blocks. One needs to develop a control strategy for the UAVs such that:

1) The UAVs can detect and follow the flood boundary autonomously.
2) The UAVs can be evenly distribute along the flood boundary, keeping a safe distance.

This constitutes the main goal of this research.

For the control strategy design, the following kinematic model for the UAVs is adopted:

$$\dot{\boldsymbol{q}}_i = \boldsymbol{u}_i + \boldsymbol{\xi}_i, \tag{1}$$

where $\boldsymbol{q}_i$ is the state (horizontal displacement) of a single UAV and $\boldsymbol{u}_i$ is the corresponding velocity controller. The control problem is to construct the controller $\boldsymbol{u}_i$ so that the corresponding $\boldsymbol{q}_i$ is consistent with the proposed control strategy. Assuming the number of UAVs is n, one has $i \in \{1, 2, ..., n\}$.

In the control problem, the kinematic model (1) is adopted as one can assume that there is a low-level controller in place to cancel existing dynamic. Higher-order dynamics can be accommodated, but the resulting complication obscures the main result [25]

III. Controller Design

The design of the controller $\boldsymbol{u}_i$ is required to realize three essential functions: the first function is to make the UAVs track the edge of a flood area and cage it; the second function is to restrict the movable range of the UAVs such that they can be located on the edge of the flood area, and the third function is to separate the UAVs from each other at a certain distance to prevent collisions. Correspondingly, the controller $\boldsymbol{u}_i$ is defined as

$$\boldsymbol{u}_i = \boldsymbol{u}_i^c + \boldsymbol{u}_i^v + \boldsymbol{u}_i^r, \tag{2}$$

where $\boldsymbol{u}_i^c$ is the velocity assigned to each UAV during the encircling process, $\boldsymbol{u}_i^v$ represents boundary tracking controller, and $\boldsymbol{u}_i^r$ represents the separation controller. The separation controller $\boldsymbol{u}_i^r$ is designed based on a potential field method, which can keep adjacent UAVs within a certain distance. The controller $\boldsymbol{u}_i^v$ for boundary tracking is designed based on an image segmentation approach. It can achieve real-time autonomous navigation of a UAV along the boundary of a flood area.

A. Design of $\boldsymbol{u}_i^v$

The vision-based adaptive boundary tracking problem for a single UAV mainly has two parts: video segmentation and robust adaptive boundary tracking. Video segmentation is used for obtaining the boundary of the flood area, which can be used by the boundary tracking controller $\boldsymbol{u}_i^v$ to autonomously navigate the UAV along the boundary of the flood area.

1) Video segmentation technique: It is important for UAVs to segment a flood area fast and accurately as most image segmentation technologies cannot satisfy the hardware requirements of mobile and embedded devices. To balance accuracy and real-time performance, we propose a novel architecture, MFFM-Net for flood segmentation. Fig. 2 (the red block is MFF Block) shows an architecture of the proposed method, composed of MobileNet, Multiscale-Fusion-Feature (MFF) Block, and Feature Pyramid Network (FPN) [26]. Specifically, to improve the real-time performance of the network, we use MobileNet to extract features and reduce the size and complexity of the MobileNet by depth deconvolution. It is particularly useful for real-time embedded vision applications. However, in deeper layer of the network, shallow features are difficult to preserve. The lack of complementary spatiotemporal feature information may affect the object recognition ability.

Shallow features have global information but lack semantic information, which may reduce their object detection a-

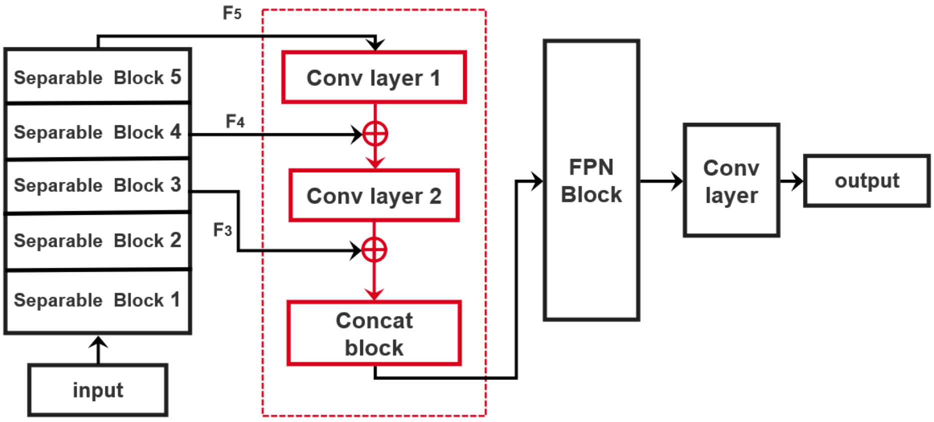

Fig. 2. The architecture of our proposed MFFM-Net.

bility for video segmentation [26]. Therefor, a feasible neural network should consider both shallow and deep features. For taking full advantage of shallow and deeper features, we propose a novel MFF Block, which is mainly used for feature fusion and feature enhancement among different feature scales. Commonly, multiscale feature representations can yield better results than single feature representation because multiscale feature representation is more informative and accurate than any single feature representation. Therefore, multiscale feature fusion is promising for these disadvantages. Using the MFF Block, the context information of features can be merged better and target feature extraction can be achieved. In the MFFM-Net, the input of MFF Block is the features extracted by Separable Block3, 4, 5. F5 is the input of the convolutionary layer 1, and the output of convolutionary layer 1 is a deeper feature. The input of convolutionary layer 2 is the combination of deeper feature and F4. A much deeper feature is obtained after being process by convolutionary layer 2 and becomes the input of Concat Block. The output of Contact Block is the desired feature map. Finally, we can obtain the desired feature map.

We propose the Concat Block to combine the shallow and deeper features, as shown in Fig. 3. The Concat Block is mainly composed of convolutionary layers and a concatenate layer. The input of the Concat Block is a feature map. The convolutionary layers can functionally extract features from feature map. The concatenate layer is used to combine several convolutionary layers. The block can improve the accuracy by increasing the depth of layer and combining the deeper features from deep layer with shallow features.

2) Robust adaptive boundary tracking control for a single UAV: Combining the image segmentation algorithm with a robust adaptive velocity controller for a single UAV is an effective method for solving the tracking problem. As shown in Fig. 4. Flood zone and non-flood zone are segmented by using the flood segmentation algorithm, where the blue zone represents the flood area. The black squared frame represents the vision field of a single UAV. The aim of the vision-based controller $\boldsymbol{u}_i^v$ is to keep the midpoint of two mass centers of land and flood area on the geometric center of the limited vision field of a single UAV. To reach the purpose, the controller $\boldsymbol{u}_i^v$ can be defined as follows.

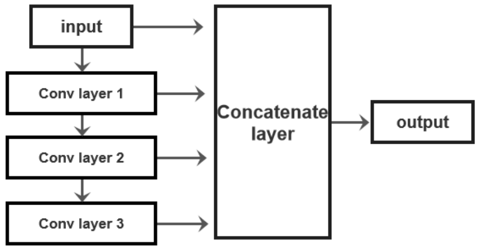

Fig. 3. The architecture of Concat Block.

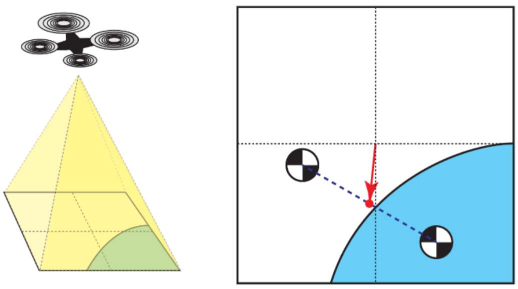

Fig. 4. Tracking problem for a single UAV.

Define $\boldsymbol{p}_i$ as the absolute position vector which is defined at the global coordinate frame for the midpoint of two mass centers of the land and the flood area. The error $\boldsymbol{e}_i$ is defined as $\boldsymbol{q}_i - \boldsymbol{p}_i$, which is the distance between a single UAV and the flood area. The corresponding error dynamics of a single UAV can be defined as

$$\dot{\boldsymbol{e}}_i = \boldsymbol{u}_i^v + \boldsymbol{d}_i, \tag{3}$$

where $\boldsymbol{d}_i = \boldsymbol{\xi}_i - \dot{\boldsymbol{p}}_i$ denotes the lumped uncertainties.

The control problem can then be stated as constructing an asymptotically stabilizing law $\boldsymbol{u}_i^v$ for the control system such that $\lim_{t\to\infty} \boldsymbol{e}_i(t) = \mathbf{0}$, in the presence of the time-varying uncertainty $\boldsymbol{d}_i$.

To deal with time-varying uncertainties in the control system, we propose a FATII based control technique, in which the uncertainty $\boldsymbol{d}_i$ in (3) is approximated as

$$\boldsymbol{d}_i(t) = \sum_{j=1}^{N} \boldsymbol{d}_{ij}\psi_j(t), \tag{4}$$

where $\boldsymbol{d}_{ij}$ denotes unknown constant vectors, $\psi_j(t)$ is the basis function, selected as the Fourier series [27] in this paper.

Substituting (4) into (3) yields

$$\dot{\boldsymbol{e}}_i = \boldsymbol{u}_i^v + \sum_{j=1}^{N} \boldsymbol{d}_{ij}\psi_j(t). \tag{5}$$

In the FATII controller design [28], to remove the unknown term $\boldsymbol{d}_{ij}$ from the expression of $\dot{\boldsymbol{e}}_i$, one defines in the extended space $(\boldsymbol{e}_i, \hat{\boldsymbol{d}}_{ij})$ the manifold

$$\mathcal{M}_i = \{(\boldsymbol{e}_i, \hat{\boldsymbol{d}}_{ij}) \in \mathbb{R}^2 \mid \boldsymbol{d}_{ij} - \hat{\boldsymbol{d}}_{ij} - \boldsymbol{\beta}_{ij} = \mathbf{0}\}, \tag{6}$$

where $\hat{\boldsymbol{d}}_{ij} \in \mathbb{R}^{n\times 1}$ (the estimation of $\boldsymbol{d}_{ij}$) and $\boldsymbol{\beta}_{ij}(\boldsymbol{e}_i, t) \in \mathbb{R}^{n\times 1}$ are functions to be specified. By defining the off-the-manifold variable $\boldsymbol{z}_{ij} = \boldsymbol{d}_{ij} - \hat{\boldsymbol{d}}_{ij} - \boldsymbol{\beta}_{ij}$ where $\boldsymbol{z}_{ij} \in \mathbb{R}^{n\times 1}$, (5) is transformed to

$$\dot{\boldsymbol{e}}_i = \boldsymbol{u}_i^v + \sum_{j=1}^{N} \big(\boldsymbol{z}_{ij} + \hat{\boldsymbol{d}}_{ij} + \boldsymbol{\beta}_{ij}\big)\psi_j, \tag{7}$$

Here, $\boldsymbol{z}_{ij} = \mathbf{0}$ implies that for each agent i, the system dynamics stays on the manifold $\mathcal{M}_i$.

The FATII based controller is then designed as

$$\begin{aligned} \boldsymbol{u}_i^v &= -k_i\boldsymbol{e}_i - \sum_{j=1}^{N}(\hat{\boldsymbol{d}}_{ij} + \boldsymbol{\beta}_{ij})\psi_j, \\ \dot{\hat{\boldsymbol{d}}}_{ij} &= -\boldsymbol{e}_i\dot{\psi}_j + k_i\boldsymbol{e}_i\psi_j, \\ \boldsymbol{\beta}_{ij} &= \boldsymbol{e}_i\psi_j, \end{aligned} \tag{8}$$

where $k_i = k + \frac{1}{4}$ and k is a positive constant.

Theorem 1: The closed loop system, formulated by (7) and (8), is asymptotically stable.

Proof: Substituting (8) into (7) yields

$$\dot{\boldsymbol{e}}_i = -k_i\boldsymbol{e}_i + \sum_{j=1}^{N} \boldsymbol{z}_{ij}\psi_j. \tag{9}$$

The derivative of $\boldsymbol{z}_i$ is computed as

$$\dot{\boldsymbol{z}}_{ij} = -\dot{\hat{\boldsymbol{d}}}_{ij} - \frac{\partial\boldsymbol{\beta}_{ij}}{\partial\boldsymbol{e}_i}\dot{\boldsymbol{e}}_i - \frac{\partial\boldsymbol{\beta}_{ij}}{\partial t} = -\psi_j\sum_{k=1}^{N}\boldsymbol{z}_{ik}\psi_k. \tag{10}$$

To prove the stability of the closed-loop system, the Lyapunov candidate function is chosen as

$$V = \frac{1}{2}\sum_{i=1}^{n}\boldsymbol{e}_i^\top\boldsymbol{e}_i + \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{N}\boldsymbol{z}_{ij}^\top\boldsymbol{z}_{ij}, \tag{11}$$

the derivative of which is calculated as

$$\dot{V} = \sum_{i=1}^{n}\boldsymbol{e}_i^\top\dot{\boldsymbol{e}}_i + \sum_{i=1}^{n}\sum_{j=1}^{N}\boldsymbol{z}_{ij}^\top\dot{\boldsymbol{z}}_{ij}. \tag{12}$$

Substituting (9) and (10) into (12) yields

$$\begin{aligned} \dot{V} =& \sum_{i=1}^{n}\boldsymbol{e}_i^\top\left(-k_i\boldsymbol{e}_i + \sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\right) \\ &- \sum_{i=1}^{n}\left(\sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\right)^\top\left(\sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\right) \\ =& \sum_{i=1}^{n}\left(\boldsymbol{e}_i^\top\Big(-k_i\boldsymbol{e}_i + \sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\Big) + \frac{1}{4}\boldsymbol{e}_i^\top\boldsymbol{e}_i\right. \\ &\left. - \frac{1}{4}\boldsymbol{e}_i^\top\boldsymbol{e}_i - \left(\sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\right)^\top\left(\sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\right)\right) \\ \le& -\sum_{i=1}^{n}\left(\left(k_i - \frac{1}{4}\right)\|\boldsymbol{e}_i\|_2^2 + \left\|\frac{1}{2}\boldsymbol{e}_i - \sum_{j=1}^{N}\boldsymbol{z}_{ij}\psi_j\right\|_2^2\right). \end{aligned}$$

By selecting $k_i = k + \frac{1}{4}$ where $k > 0$, $\dot{V}$ is negative semi-definite. According to the Barbalat's lemma [29], both the state and the estimation error converge to zero. ■

After the single UAV control is achieved, a formation control algorithm is proposed to deal with a group of UAVs control.

B. Design of $\boldsymbol{u}_i^r$

During the caging process, to avoid collision between UAVs, it is necessary to ensure that the adjacent UAVs keep a specific distance among their neighbors. If the distance is too small, UAVs need be separated. Due to the limitation of communication range, if the distance between the adjacent UAVs is larger than the limitation distance, the interaction will disappear. To meet these requirements, the separating controller $\boldsymbol{u}_i^r$ can be defined as follows:

$$\boldsymbol{u}_i^r = \begin{cases} \sum_{h=1, h\neq i}^{N}\Big(1 - \beta(\|\boldsymbol{q}_i - \boldsymbol{q}_h\|)\Big)\boldsymbol{v}_i, & \|\boldsymbol{q}_i - \boldsymbol{q}_h\| \le d \\ \mathbf{0}, & \|\boldsymbol{q}_i - \boldsymbol{q}_h\| > d \end{cases} \tag{13}$$

where in $\beta(.)$ of (13) is the 4th order Beta function expressed by

$$\begin{aligned} \beta = \frac{35}{d^4}\|\boldsymbol{q}_i - \boldsymbol{q}_h\|^4 - \frac{84}{d^5}\|\boldsymbol{q}_i - \boldsymbol{q}_h\|^5 \\ + \frac{70}{d^6}\|\boldsymbol{q}_i - \boldsymbol{q}_h\|^6 - \frac{20}{d^7}\|\boldsymbol{q}_i - \boldsymbol{q}_h\|^7, \end{aligned} \tag{14}$$

and $\boldsymbol{v}_i$ is a constant vector that weights β. Based on (14), if the distance between a single UAV i and neighbor h is less than a specific distance value d, UAV i will move away from neighbor h. On the contrary, if the distance value is compared with d, the distance value is larger, then the magnitude of $\boldsymbol{u}_i^r$ will be zero.

C. Combined control algorithm for UAVs

To cage the flood by multiple UAVs, we combine the flocking-based formation control with the adaptive vision-based tracking algorithms. The algorithm is effective when both flood and land areas are in the limited field of vision of a single UAV. If the vision is filled with only land or flood area, the UAV will continue to increase its height, and the limited field of vision of a UAV will be enlarged. The UAV will stop rising until the flood and land area are observed at the same time. The combined control algorithm can be summarized as the Algorithm1.

Algorithm 1

Input: $\boldsymbol{u}_i$

Output: $\boldsymbol{q}_i$

Initialization: $\boldsymbol{u}_i = \boldsymbol{q}_i = \boldsymbol{0}$, obtain images from each camera of UAV

Repeat:

if Both a land and a flood area appear in the limited field of vision of a single UAV **then**

  Calculate the position vector $\boldsymbol{p}_i$ from the limited field of vision of a single UAV

  The controller $\boldsymbol{u}_i^v$ will be updated by using (8)

  The state vector $\boldsymbol{q}_i$ can be updated by (1), and the $\boldsymbol{u}_i^r$ will be selected for (13). The $\boldsymbol{u}_i^r$ can be a tangent vector to the edge of the flood area

  A new image from a camera of a UAV will be obtained.

else

  The height of a UAV is increased.

end if

End

IV. Case study

To verify the effectiveness of the control strategy, we conduct the following simulations under the ROS/Gazebo programming environment. A group of UAVs are modified by using the Hector quadrotor package [30], which has been collected into the ROS stacks, and the ROS stacks support simulation and interaction between UAVs and environment (flood) .

In the simulation, the flood is represented by a lake image from real world and 10 UAVs are used to track the boundary of a flood area. The simulation lasts for 100 seconds. The velocity of each UAV is 1m/s. The maximum distance d in the Beta-function (14) is chosen to be 10m.

MFFM-Net is trained on the River dataset [31]. The dataset contains 300 original images of different rivers, and the corresponding labeled images are given. The water and background of the labeled images are respectively composed of a two-dimensional binary matrix. To prevent the fitting from an insufficient training set, we collect some pictures from the Internet and take some pictures to expand them into the training set. Moreover, we use data enhancement technology to extend the training set by rotating, clipping, and shifting the dataset.

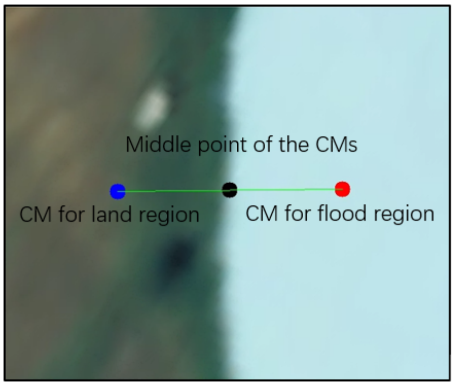

Fig. 5. Camera image of a UAV during the caging stage.

Moreover, due to the memory limitation, the original images are split into a patch size of 512 x 512. In this paper, we use the K-fold [32] cross validation algorithm to avoid overfitting of data. The basic idea is to divide the original training set into two sets: one is a new training set within 9 folds, another one is a validation set within 1 fold. The new training set is used to train the network, and the validation set is used to validate its error. Then the steps are repeated 10 times until all the elements are selected once. The learning rate is set to be 0.001, the optimizer we used is Adam, and values of β_1 and β_2 are 0.9 and 0.999, respectively.

The image of the limited vision field of a UAV is shown in Fig. 5. The blue areas and the rest portion respectively represent the flood and the land area, the blue and red dots are their Center of Mass(CMs), and the black dot represents the center of two CMs. Based on the vision-based boundary tracking algorithm III-C which we have proposed, the black dot will move to the geometric center of the limited field of vision of a single UAV such that UAVs can track the boundary of a flood area.

As shown in Fig. 6. under the proposed controller the drones, represent by the yellow box, successfully caged a flood area in an irregular shape.

V. Conclusion

A control strategy has been proposed for caging a flood area via multiple UAVs. The strategy consists of two parts. One is vision-based adaptive control that allows each UAV to detect and follow the boundary of the flood area. The other is flocking based formation control which uniformly distributes UAVs along the flood boundary without collisions among neighbours. The proposed strategy has been verified through simulations under the ROS/Gazebo environment. In future work, we will continue to conduct experiments in the real world in order to further verify the effectiveness of our strategy.

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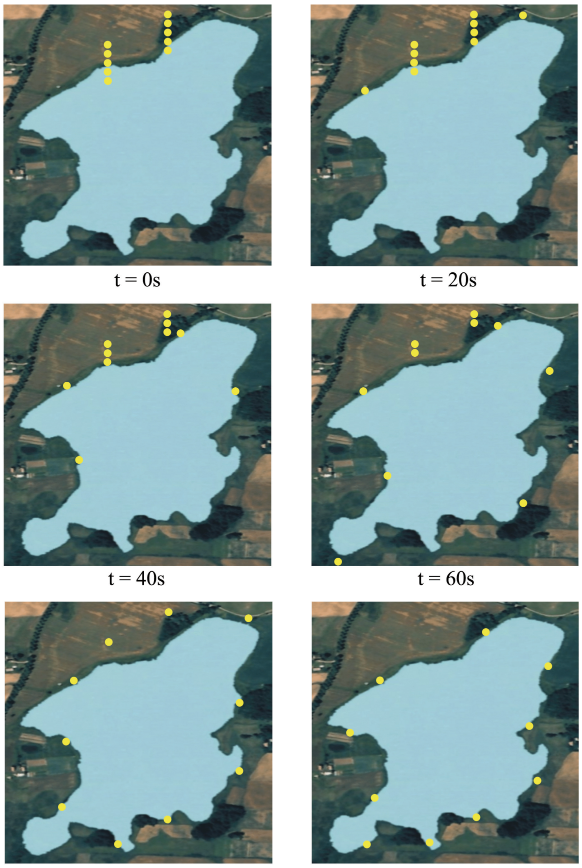

Fig. 6. A group of UAVs (yellow) cage and track a flood area. A birds' eye view of the Large Setal Lake. Source: J. Mialdun.

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