THE 2ND ANTI-UAV WORKSHOP & CHALLENGE: METHODS AND RESULTS

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ABSTRACT

The 2nd Anti-UAV Workshop & Challenge aims to encourage research in developing novel and accurate methods for multi-scale object tracking. The Anti-UAV dataset used for the Anti-UAV Challenge has been publicly released. There are two subsets in the dataset, i.e., the test-dev subset and test-challenge subset. Both subsets consist of 140 thermal infrared video sequences, spanning multiple occurrences of multi-scale UAVs. Around 24 participating teams from the globe competed in the 2nd Anti-UAV Challenge. In this paper, we provide a brief summary of the 2nd Anti-UAV Workshop & Challenge including brief introductions to the top three methods. The submission leaderboard will be reopened for researchers that are interested in the Anti-UAV challenge. The benchmark dataset and other information can be found at: https://anti-uav.github.io/.

Keywords Object Tracking, UAV, Multi-scale, Infrared Video

1 Introduction

Civil unmanned aerial vehicle (UAV) is growing rapidly in a wide range of consumer communications and networks with their autonomy, flexibility, and a broad range of application domains. UAV applications offer possible civil and public domain applications in which single or multiple UAVs may be used. Nevertheless, we should also be aware of the potential threat to our lives caused by UAV intrusion, since UAVs can also be used to conduct physical attacks (e.g., via explosives) and cyber-attacks (e.g., hacking a critical infrastructure). Moreover, unauthorized UAVs are a danger to civilian aircraft. There have been multiple instances of drone sightings that halted air traffic at airports, leading to significant economic losses for airlines.

Historically, radar is certainly a very powerful technology for detecting traditional incoming airborne threats. However, these comparatively small drones are difficult for radar to accurately detect, because they have very small radar cross-sections and erratic flight paths. Therefore, how to use computer vision algorithms to perceive UAVs is a crucial part of the whole UAV-defense system.

Traditional computer vision research [8] [9] [10] [11] [12] for UAV detection and tracking lacks a high-quality benchmark in dynamic environments. To mitigate this gap, we held the 1st International Workshop on Anti-UAV
Challenge [13] at CVPR 2020, releasing a dataset consisting of 160 video sequences (both RGB and infrared). The workshop attracted attention from researchers all over the world. Many submitted solutions outperform the baseline method, making great contributions to addressing the anti-UAV problem [13] [14] [15]. The 2nd anti-UAV challenge extends the benchmark dataset to 280 high-quality, full HD thermal infrared video sequences, spanning multiple occurrences of multi-scale (i.e., large, small and tiny, as shown in Fig.1) UAVs. The workshop encourages participants to develop automated methods that can detect and track UAVs in thermal infrared videos with high accuracy. Particularly, algorithms that can detect and track fast-moving drones in complex environments (e.g., occlusion by cloud/buildings/trees, and fake targets like kites, balloons, birds, etc.) are highly expected.

This workshop will bring together academic and industrial experts in the field of UAVs to discuss the techniques and applications of tracking UAVs. Participants are invited to submit their original contributions, surveys, and case studies that address the works of UAV’s detection and tracking issues.

![Figure 1: Illustrations of civil UAVs: Large civil UAV; Small civil UAV; Tiny civil UAV.](image)

### 2 The ANTI-UAV Challenge

#### 2.1 Dataset

There are two subsets in the dataset, i.e., the test-dev subset and test-challenge subset. Both subsets consist of 140 thermal infrared video sequences, spanning multiple occurrences of multi-scale UAVs. We only provide annotation files for the test-dev. Compared to the previous challenge, we enlarge both the test-dev and the test-challenge in this year by adding more challenging video sequences with dynamic backgrounds and small-scale targets, such that the resulting new dataset covers a greater variety of scenarios with multi-scale UAVs. The target scales include large, medium, small, and tiny. Besides, The videos recorded include two lighting conditions (day and night), and diverse backgrounds (buildings, cloud, trees, sea, etc.).

#### 2.2 Metric

Anti-UAV is annotated with bounding boxes, attributes and existing flags. Moreover, an empty bounding box list denotes a ”not exist” flag. Trackers need to obtain the perception of UAV status. In this case, the presence of UAV in the visual range is introduced into the evaluation metric:

\[
acc = \frac{\sum_{t=1}^{T} IoU_t \times 1 [v_t > 0] + p_t \times (1 - 1 [v_t > 0])}{T},
\]

For frame \( t \), \( IoU_t \) is Intersection over Union (IoU) between the predicted tracking box and its corresponding ground-truth box, \( p_t \) equals 1 when the predicted box is empty and 0 otherwise, and \( v_t \) is the ground-truth existence/visibility flag of the target. The Iverson bracket indicator function \( 1 [v_t > 0] \) equals 1 when \( v_t > 0 \) and 0 otherwise. The accuracy is averaged over all \( T \) frames.

### 3 Result and Method

The 2nd Anti-UAV challenge was held between May 12, 2021 and July 10, 2021. The results of the 2nd Anti-UAV challenge are shown in Table 1. Around 24 teams submitted their final results in this challenge. In this section, we will briefly introduce the methodologies of the top 3 submissions.
### Table 1: Challenge results

| Rank | User Name                        | Tracking Accuracy |
|------|----------------------------------|-------------------|
| 1    | huangbo940326                    | 0.6444            |
| 2    | whoamiw                          | 0.6388            |
| 3    | JUN                              | 0.6380            |
| 4    | tang_god                         | 0.6356            |
| 5    | ZhangyongTang                    | 0.6215            |
| 6    | QLY                              | 0.6130            |
| 7    | jjchen                           | 0.6116            |
| 8    | blue_star                        | 0.6116            |
| 9    | hli1221                          | 0.6082            |
| 10   | zhangxiaohan_zhaojinjian         | 0.6066            |
| 11   | YouKnowWhoAmI                    | 0.6062            |
| 12   | leili                            | 0.5848            |
| 13   | guyu                             | 0.5824            |
| 14   | jinke                            | 0.5795            |
| 15   | xjtduz                           | 0.5752            |
| 16   | shan666                          | 0.5681            |
| 17   | adamzdw                          | 0.5603            |
| 18   | Homura                           | 0.5544            |
| 19   | jkahsjdk                         | 0.5251            |
| 20   | ywang26                          | 0.5163            |
| 21   | Nitre                            | 0.5139            |
| 22   | zhuwenming                       | 0.5057            |
| 23   | tangyuan23                       | 0.4941            |
| 24   | kostadinov                       | 0.4930            |

3.1 Team BIT_OITS

Bo Huang, Junjie Chen, Shenwang Jiang, Ying Wang, Yuncheng Wang, Lei Wang, Tingfa Xu. (Beijing Institute of Technology (BIT) & Beijing Institute of Technology Chongqing Innovation Center (BITCQIC))

The authors propose a robust spatio-temporal attention based Siamese (SiamSTA) tracker to track UAV targets in thermal infrared (TIR) videos. The SiamSTA tracker is built on the Siam R-CNN [1] network, and they borrow the pre-trained weights from Siam R-CNN. Like other Siamese frameworks, SiamSTA also consists of two branches: a template branch that is initialized by the first frame and a test branch that feeds the current detecting image. These two branches share the same weights, and are followed by a two-stage re-detector to compute the confidence scores for the enumeration of multiple RPN proposals.

Siam R-CNN. In Siam R-CNN, the authors develop a tracklet dynamic programming algorithm (TDPA) to implicitly track both the object of interest and potential similar-looking distractors using spatio-temporal cues. A tracklet means a trajectory which consists of a sequence of non-overlapping trajectories. Siam R-CNN backs up a lot of such tracklets to filter the optimal predicted bounding box from thousands of candidate proposals. The same knife cuts bread and fingers.

SiamSTA Tracker Design. For a tracking task in TIR videos, the object is often textureless, especially for far-range drone planar argets. In some extreme cases, the drone target is very small, even like a point target, and there will be a plethora of distractors in the scene. At this time, these tracklets may bring additional interference due to the difficulty of extracting high-quality semantic features for the weak UAV targets. To address such issue, finer exploitation of spatio-temporal attention mechanisms is a feasible solution. The SiamSTA tracker is designed as following: Firstly, the tracker records the target’s size, ratio for all previous frames, and the new predicted tracklets must be within the range of \([0.8 \times \min(size), 1.2 \times \max(size)]\), \([0.8 \times \min(ratio), 1.2 \times \max(ratio)]\). Other tracklets are treated as background distractors and will be terminated directly. The authors then develop an optical flow-based algorithm to estimate global background motion. They use the ShiTomasi algorithm to compute the key points, and constrain the number of key points in the range of 5-30. They then apply the Lucas-Kanade (L-K) optical flow to track these key points, and select the points whose forward-backward (F-B) error is less than 1. If the average location diff of these selected key points is less than 0.5 for 5 consecutive frames, they consider the camera to be static. Under a long-range static camera, they assume that there are no huge position jumps for these targets between two adjacent frames, thus they can obtain a more
reliable tracking result by searching the nearby area. In this case, authors set the overlap of two consecutive tracklets to be greater than 0.1, they will delete the other tracklets.

**Model Refinement.** However, if the target is lost, using the nearby detecting strategy will cause the model to fail completely. In order to cope with the target loss, especially when handling the challenge of target occlusion or out of view, a mature global re-detection becomes necessary to recover the tracking failures. Therefore, it is very critical to define the boundaries of nearby tracking and global re-detection to improve tracking performance. If the background is dynamic and the re-detection score is greater than 0, authors output the tracklet with the best score. On the contrast, they implement the change detection algorithms from the pybgs library: one is FrameDifference, the other is DPGrimsonGMM. If the output of tracklets, FrameDifference and DPGrimsonGMM have a large overlap, they believe that the tracking result is surely correct, and they will use nearby detecting in the next frame. If the output of FrameDifference and DPGrimsonGMM have a large overlap, but the location of tracklets is isolated, authors believe that the tracklets fail and add a new tracklet initialized by moving target detection. If there is no overlap for these three tracking results, authors output the bounding box of tracklet with the best score, and they will perform a global re-detection in the next frame.

**Ablation study.** Authors do ablation experiments to verify the effect of each incremental component, including lost definition, change detection (CD), and spatio temporal attention (STA). They provide six sets of tracking results which are described as follows:

- Siam RCNN Baseline: it is the same method as Siam RCNN without changing anything.
- Siam RCNN Lost: they add a lost definition to Siam RCNN, if the score of the best tracklet is less than 0.0, they consider the tracking to be a failure and output the empty result.
- Siam RCNN + STA: they add the spatio temporal constraints mentioned above to Siam RCNN. In addition, if the score of the best tracklet is greater than 0.9, they perform a nearby searching, and otherwise they will do a global re-detection.
- Siam RCNN + CD: they utilize the change detection method to re capture the target, tracklets with a large overlap with change detection results will be assigned a high score, and untrustworthy tracklets will be deleted directly.
- CD + STA: this is a pure motion detection tracker without Siam RCNN. To cope with the background motion and target jump, they add the same spatio temporal constraints and introduce a correlation filter based algorithm to assist the tracking.
- Siam RCNN + STA + CD: this is their final method as previously stated.

**Main contribution.** Authors propose several practical guidelines to solve the challenge of drone tracking, such as weak targets, small targets. Their tracker makes full use of prior knowledge like scale/ratio distribution by combining neighborhood search and global detection. The proposed CD+STA algorithm fully exploits valuable motion information, which can greatly benefit the tracking of tiny moving drone targets.

### 3.2 Team COLA Try

**Zitian Wang, Shangzhe Di, Zongheng Tang, Si Liu.** (Beihang University)

Authors adapted some recent trackers (like ECO [2], KYS, SuperDiMP [3] and Stark) to the LTMU [4] long-term tracking framework, with pluggable AlphaRef [5] for scale estimation. These trackers are built for producing more robust tracking results through the multi-tracker voting and fusion. Specifically, for each frame, all the trackers first produce the tracking results respectively, then an IOU-based clustering algorithm is applied to generate a set of clusters. The box and confidence of each cluster are reweighted by the elements belonging to this cluster and the cluster size. The cluster with the highest confidence will serve as the final prediction of this frame. They also adopted the motion enhancement to distinguish small UAVs from background noises. First, optical flow is predicted between adjacent frames. Optical flow mainly captures the camera movement between adjacent frames, while ignoring the UAV movement due to the very small size. Then the image warping based on optical flow is to make the background in adjacent frames more aligned. So they use a background subtraction method to capture the motion pattern of the two frames. The output motion activation map serve as prior knowledge which indicates the moving small UAVs, and is fused with original frame for motion enhancement.

**Ablation study.**

- SuperDiMP + AlphaRef -> 60.6
- SuperDiMP + AlphaRef + LTMU -> 64.0
- Stark -> 60.6
- Stark + AlphaRef -> 62.1
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- Stark + AlphaRef + LTMU -> 63.1
- multi-tracker voting and fusion -> 67.5
- +motion enhancement -> 68.7

Main contribution. Since the organizers require that "test-dev" data should not be used for training and no detector should be applied, authors consider the problem from the perspective of exploiting trackers trained in another domain (RGB input, general scenes) to track UAVs with IR input. They proposed multi-tracker voting and fusion (can be seen as one kind of ensemble) to make the most of different tracking mechanisms and generate more robust tracking results. On the other hand, the pretrained trackers struggled to track the small UAVs with background noises due to unseen scenarios and poor appearance information. The motion enhancement method is meant to better find these small UAVs using the motion information.

3.3 Team JNU

Xuefeng Zhu, Zhangyong Tang, Hui Li, Tianyang Xu, Xiaojun Wu, Josef Kittler. (Jiangnan University & University of Surrey)

This tracker is improved based on SuperDiMP [3], SiamRPN++ [6] and TransT [7] methods. Above all, the target state is predicted normally by detecting multi-scale search regions using a local tracker that combines SuperDiMP, TransT, and SiamRPN++ methods. Then the local result is verified by taking into account the predicted target appearance and response scores of the local tracker. If the verification result indicates that the result is correct, the normal local tracking is conducted in next frame. Otherwise, the re-detection module will be activated. Authors adopt a violent method to search the whole image by sliding windows, to determine whether the target is present and to recapture the lost target by detecting each sliding window if the target exists. Besides, the motion information provided by optical flow is also employed for target re-detection.

Ablation study.
- superDiMP -> 56.3
- Multi-scale superDiMP -> 61.1
- Multi-scale superDiMP + SiamPRN++ -> 62.7
- Multi-scale superDiMP + TansT + SiamRPN++ -> 64.0
- Multi-scale SuperDiMP + TansT+ SiamRPN++ + Re-detection -> 67.9

4 Conclusions

Object detection and tracking in the wild scenarios are fundamental yet challenging problems in computer vision. We held the 2nd Anti-UAV Challenge to encourage researchers from the fields of object detection, visual tracking and other disciplines to present their progress, communication and novel ideas that will potentially shape the future of the UAV detection area. Approximately 24 teams around the globe participated in this competition, in which top-3 leading teams, together with their methods, are briefly introduced in this paper. Our workshop takes a different perspective, making UAVs as tracking targets, and provides a large-scale dataset to promote deep network learning for UAVs. In addition, the proposed workshop also aims at tiny object detection and tracking in the wild which is more challenging, more practical, and more useful for real applications. Thus, our workshop will bridge the needs of industry and research in academia, and may accelerate the process of these computer vision technologies being used in real applications.

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