# Effect of Annotation Errors on Drone Detection with YOLOv3

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## Outline

Introduction

Performance of YOLOv3 on Anti-UAV Dataset

Performance of YOLOv3 with Simulated Annotation Errors

Annotation Correction

Conclusion



## Introduction

The main aims of this study are,

 Understanding the effects of annotation errors in a training set for object detection

 Automatically detecting and correcting annotation errors in any tracking dataset with a ground truth



## Introduction

UAV detection by fine tuning YOLOv3[1]

• Bad results due to annotation errors

What about correcting them?

[1]: Joseph Redmon and Ali Farhadi. Yolov3: An incremental improvement. CoRR, abs/1804.02767, 2018



Only thermal images of test-dev dataset is used

- 70 videos -> Training Set
- 30 videos -> Validation Set

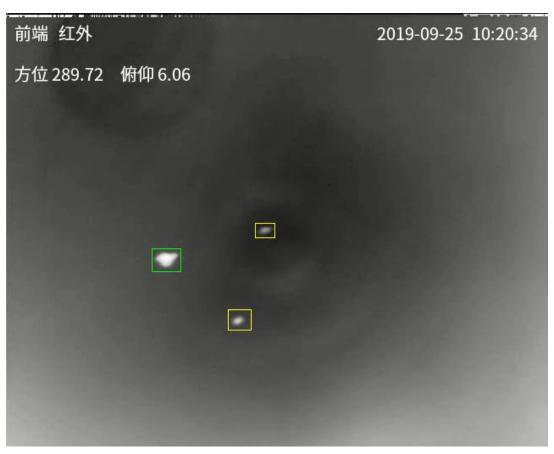


- Metrics used to measure performance:
  - Hit: IoU between detection output and ground truth > 0.5
  - Hit Rate:  $\frac{\# of \ hits}{\# of \ positive \ samples}$
  - False Alarm: IoU between detection output and ground truth = 0
  - False Alarm Per Minute: # of false alarms/minute through all samples
  - Tracking Accuracy:  $\frac{1}{T}\sum_{t=1}^{T}IoU_t*v_t*p_t+(1-p_t)(1-v_t)$   $v_t$ : Visibility Flag  $p_t$ : Prediction Flag
  - Modified Tracking Accuracy:  $\frac{\sum_{t=1}^{T} IoU_t * v_t * p_t + (1-p_t) * (1-v_t)}{\sum_{t=1}^{T} max(v_t, p_t) + (1-p_t) * (1-v_t)}$



Modified Tracking Accuracy:

$$\frac{\sum_{t=1}^{T} IoU_t * v_t * p_t + (1-p_t) * (1-v_t)}{\sum_{t=1}^{T} max(v_t, p_t) + (1-p_t) * (1-v_t)} \quad \begin{array}{c} v_t : \text{Visibility Flag} \\ p_t : \text{Prediction Flag} \end{array}$$



• Objectness Threshold = 0.5

• Hit Rate: 97.5%

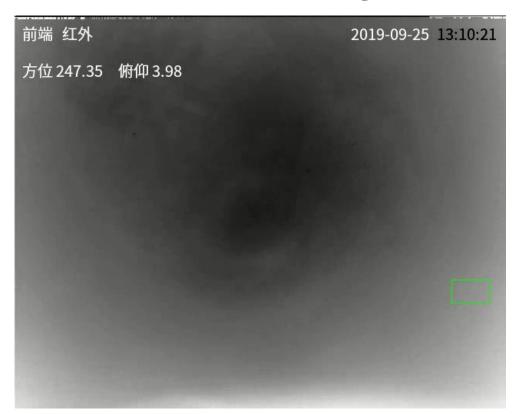
• False Alarm Per Min: 2.4

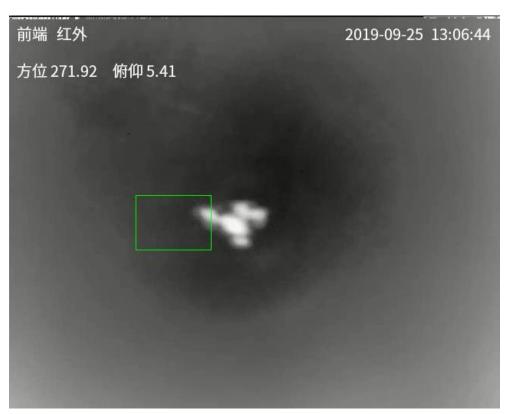
• Tracking Accuracy: 73.6%

Modified Tracking Accuracy: 73.5%



 Target detection and tracking results are quite acceptable, but not accurate due to existing annotation errors in the dataset

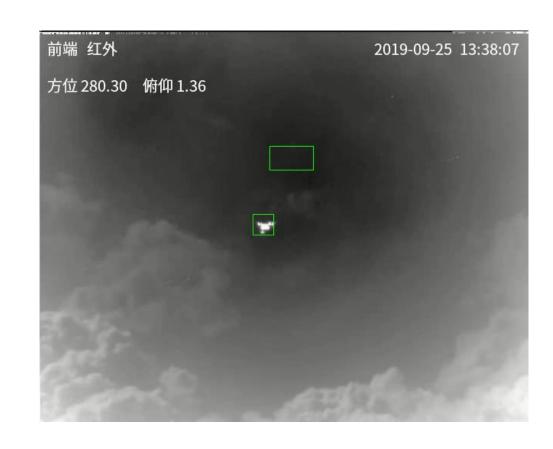






1) Additional Boxes: An extra box which does not contain any target

- Two types of additional boxes:
  - Temporarily Consistent
    - Random additional box created in one frame
    - This box tracked in consecutive frames
  - Completely Random
    - New random additional box created in each frame with a probability p





2) Missing Boxes: Unavailability of the annotation of a true object

- Two types of missing boxes:
  - Temporarily Consistent
    - Boxes are missing in consecutive frames
  - Completely Random
    - Each box can be a missing box with a probability p





3) Shifted Boxes: Slightly translated version of the true object box

• Gaussian noise  $(0, \sigma)$  added to the center of the each box.

Sizes of the boxes stay same.





	FA	HR	TA	MTA
Original Annotations	2.4	97.5	73.6	73.5
Additional Boxes (25%)	9.7	97.8	74.9	74.3
Additional Boxes (50%)	18.8	95.6	69.4	68.6
Tmp. Cons. Add. Box. (25%)	5.6	96.5	72.7	72.5
Missing Boxes (25%)	0.3	94.1	71.3	71.3
Tmp. Cons. Mss. Box. (25%)	1.0	83.2	62.5	62.4
Tmp. Cons. Mss. Box. (50%)	0.9	34.7	27.2	27.2
Shifted Boxes ( $\sigma = 1.5$ )	2.2	90.8	68.8	68.8
Shifted Boxes ( $\sigma = 10\%$ )	1.1	29.9	23.3	23.3
Combined	2.3	71.2	54.2	54.2

When Objectness Threshold is fixed to 0.5

	Thrs	HR	TA	MTA
Original Annotations	0.5	97.5	73.6	73.5
Additional Boxes (25%)	0.72	94.1	72.1	72
Additional Boxes (50%)	0.68	92.2	67	66.9
Tmp. Cons. Add. Box. (25%)	0.58	95.6	72	72
Missing Boxes (25%)	0.4	97.2	73.2	73.1
Tmp. Cons. Mss. Box. (25%)	0.38	90.8	67.9	67.8
Tmp. Cons. Mss. Box. (50%)	0.3	56	43.2	43.1
Shifted Boxes ( $\sigma = 1.5$ )	0.48	92.4	70	69.9
Shifted Boxes ( $\sigma = 10\%$ )	0.3	87.8	64.8	64.7
Combined	0.49	72.8	55.4	55.3

When FA/min is fixed to 2.4

#### Proposed solution:

Conventional template matching

#### Assumptions:

- No missing and additional boxes
- Appearance of the object does not change significantly between consecutive frames

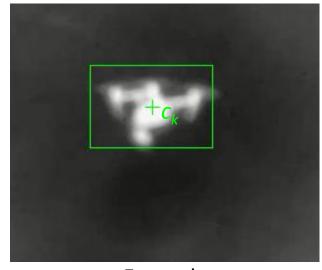
#### If the assumptions hold:

Shifted box errors can be recovered using consecutive frames

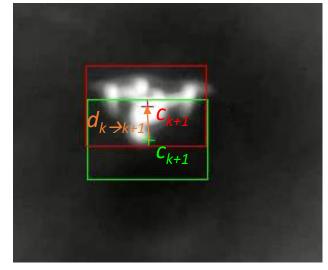


Let  $c_k$  be the object center at frame k

- Get the object template at frame k centered at  $c_k$
- Search the template around  $c_{k+1}$  on frame k+1 using normalized cross correlation to find the displacement  $d_{k\rightarrow k+1}$
- Find the displacement  $d_{k+1 \rightarrow k}$
- If  $d_{k \to k+1}$  and  $d_{k+1 \to k}$  are consistent and correlation score is above selected threshold record the displacement, otherwise break the track
- If frame k+1 has no annotated objects, break the track



Frame k



Frame k+1



For a track starting at frame k, corrected center at frame k+n

$$\hat{c}_{k+n} = \hat{c}_k + \sum_{t=k}^{k+n-1} d_{t \to t+1}$$

#### Assumption:

Displacements should have zero mean

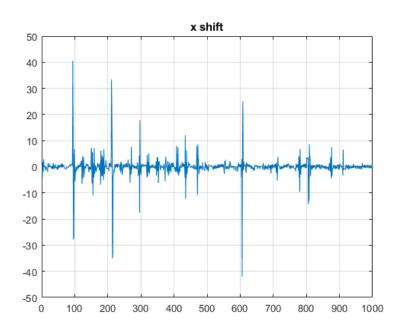
#### Problem:

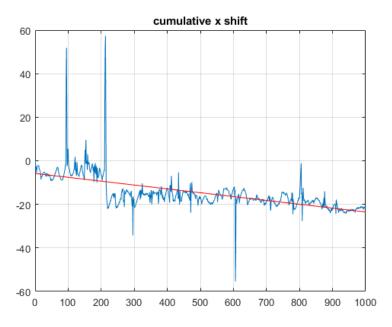
• Errors in  $d_{k \rightarrow k+1}$  are accumulated

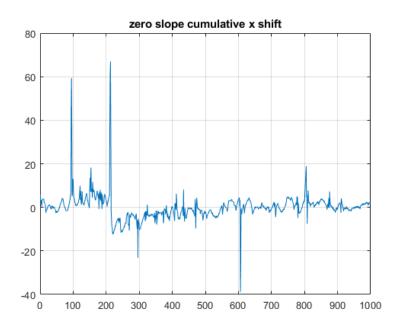
#### Solution:

Remove the trend of accumulative displacement



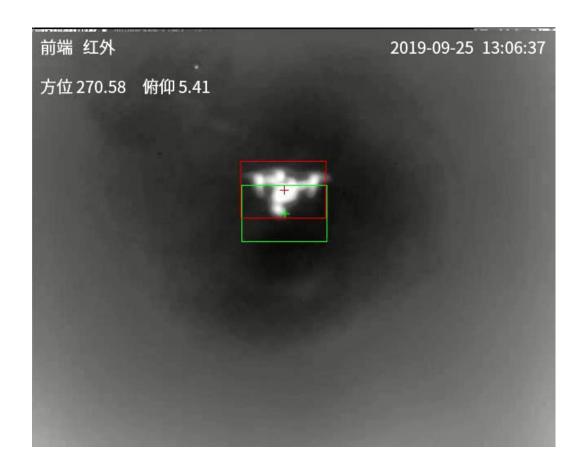




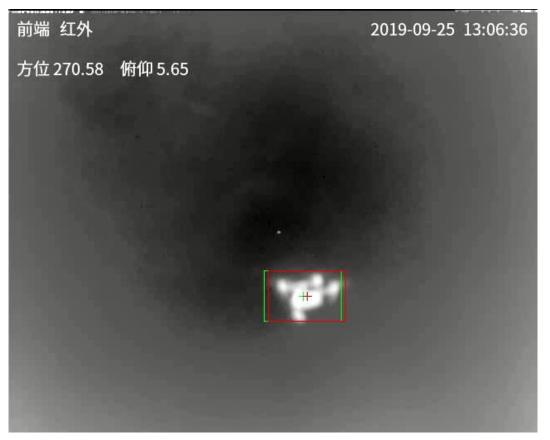












- Annotation correction applied 100 videos on Anti-UAV dataset
- Human subjects preferred corrected annotations on 66 videos
- 34 remaining videos are left with original annotations

	Thrs	HR	TA	MTA
Original Annotations	0.5	97.5	73.6	73.5
Corrected (Training Set)	0.55	98.0	74.8	74.7
Corrected (Training + Val Set)	0.55	98.8	76.3	76.2

When FA/min is fixed to 2.4



## Conclusion

- Performance of YOLOv3 on Anti-UAV dataset is relatively well.
  - Good in terms of hit and false alarm rates, not great in terms of tracking accuracy.
- Annotation errors degrade performance
- Shifted box errors are corrected with a semi-automated method
  - Results got better.
- Calculating IoU between corrected annotations and original annotations, we get 86.4% tracking accuracy
  - An algorithm which has a generalization ability can reach a maximum of 86.4% tracking accuracy (without memorizing)



## Thank You!