UUCT - HyMP: Towards Tracking Dispersed Crowd Groups from UAVs

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- Introduction and Motivation

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To tackle these issues, we propose a novel dataset and benchmark, followed by a tracking algorithm that learns end-to-end.

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  - Rich in crowd-specific attributes
  - Evaluated on existing tracking algorithms and HyMP

Simulator

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  - The complexity of the level design can be increased to make the benchmark more difficult in the future

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- We will demonstrate the entire process at the end, stay tuned!

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  - Move around the world to capture images of crowd groups
  - Possible to maintain stable viewpoint at static height as well

Ground Truth Generation Pseudo code

```
define compute_ground_truth(crowd_bounding_boxes, overlap_threshold, max_iterations):

     filtered_boxes = {}

     while current_iteration < max_iterations:
          foreach box in crowd_bounding_boxes:
               foreach other_box ≠ box in crowd_bounding_boxes:
                    if overlap ≥ overlap_threshold:
                         combine box and other_box into one box
                    else:
                         pick the box with the highest area
                         discard the other box with smaller area
                         add the picked box to filtered_boxes

          crowd_bounding_boxes = filtered_boxes
          current_iteration += 1

     if filtered_boxes.length() is 1:
          return filtered_boxes[0]
     else:
          return the box in filtered_boxes with the largest area

end compute_ground_truth
```

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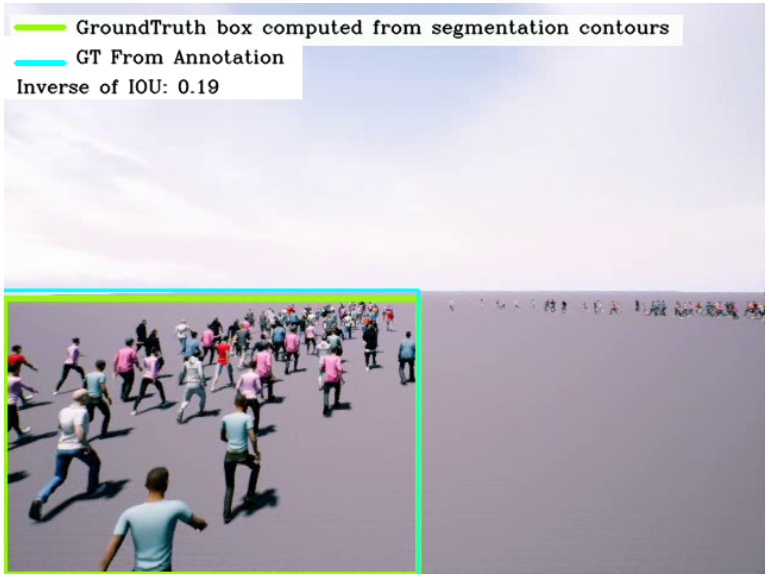
- Compute 1 - IOU (Inverse of IOU / Overlap Error)
- Compute the average of errors in each sequence of frames

Ground Truth Results



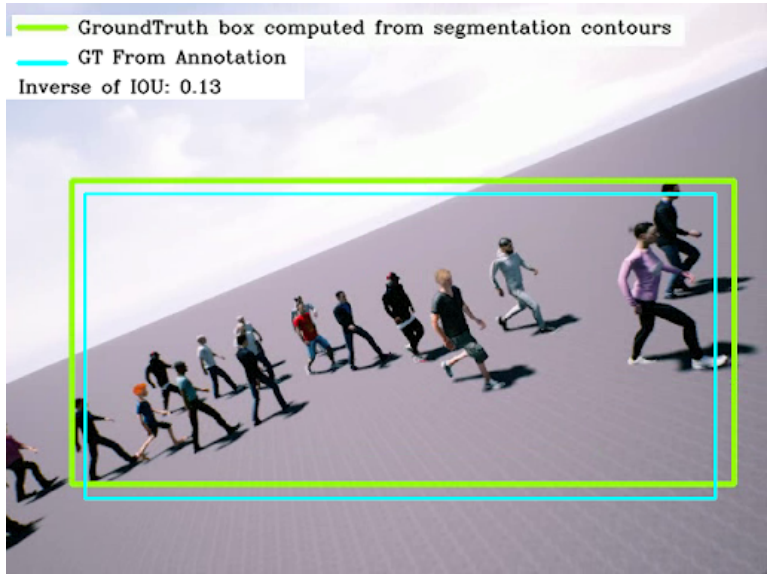


Figure: Good cases where human annotation and computed ground truth agree

Ground Truth Results (continued)

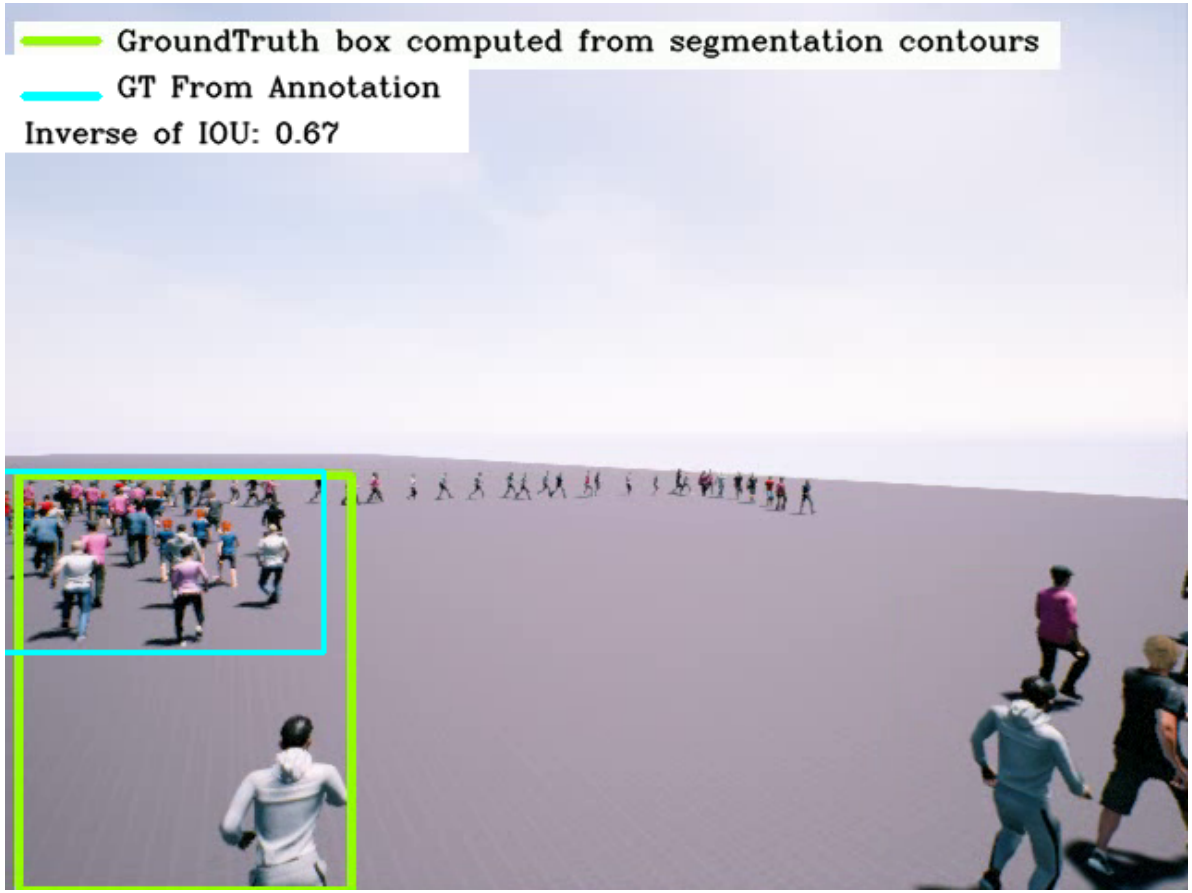


Figure: The algorithm picks a larger box, where human annotator believes the person at the bottom should be skipped for a proper box

Ground Truth Results (continued)

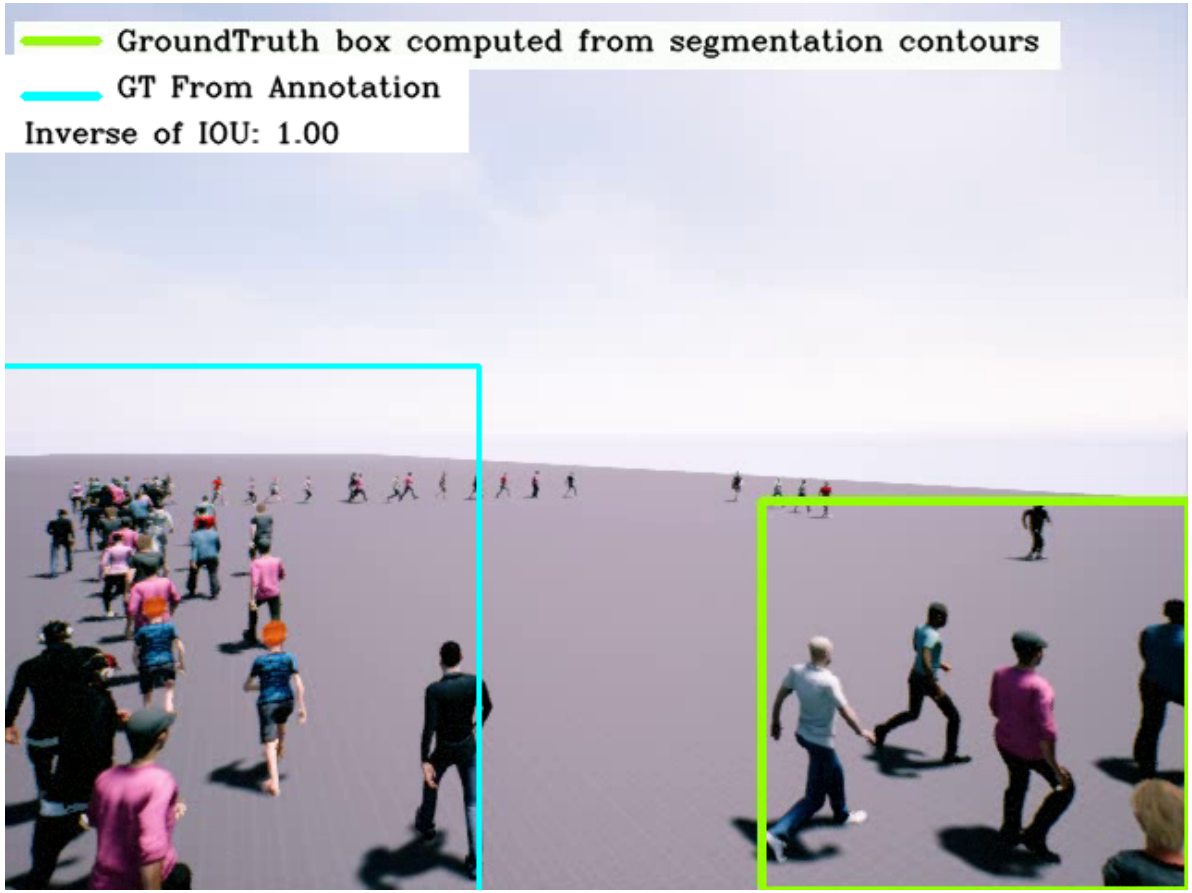


Figure: The algorithm fails to pick the proper groups of crowds and ends up selecting a smaller crowd group

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  - can also maintain a stable bounding box on the target for a longer time
  - visual servoing techniques are benefitted from stability of the bounding box

Our Tracking Algorithm: Hybrid Motion Pooling

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- Solution: Incorporate Spatio-Temporal Graphs!

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- $\Phi_{t_{ij}}^S \in \mathbb{R}^{n\times n}$ is spatial adjacency matrix. $\zeta_t^{ij} = IoU(b_t^i, b_t^j)$

Adaptive Crowd Group Learning

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- $\Phi^{ST} \in \mathbb{R}^{N \times N}$ is composed of Φ^{S}_{t} and Φ^{T}_{t}
- Update using GCN and get $\Lambda \in \mathbb{R}^{T \times dm}$:

$$\mathbb{C}^{l+1} = \sigma(\mathbb{C}^{l} + \lambda^{-\frac{1}{2}} \Phi^{ST} \lambda^{-\frac{1}{2}} \mathbb{C}^{l} W^{l})$$

Hybrid Motion Pooling

- Combine Λ with f from DiMP at each timestep using low-rank bilinear pooling as:

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- $$\kappa(v, c) = \begin{cases} v - c, & \text{if } c > \varepsilon \\ \max(0, c), & \text{otherwise} \end{cases}$$
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- ℓ_{bb} is learned according to IoU overlap

Online Tracking and Algorithm

Algorithm 1 Online HyMP Tracking Algorithm

Input : Initial Trained Model weight ∂_T, Initial Test sample $\chi_{test} = (v_0, c_0)$. New frames v_q where $q > 0$

Output: Estimated new positions with updated model

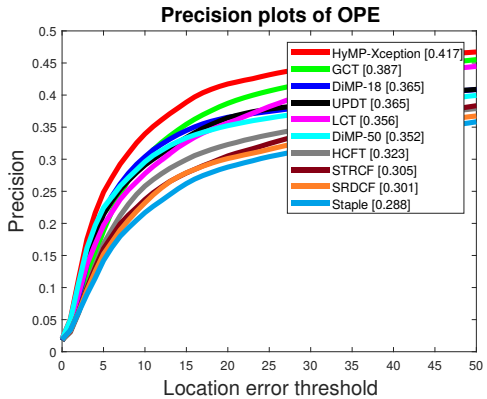
$\chi_{sample} \leftarrow$ augment $\chi_{test} = (v_0, c_0)$ pair into 10 samples
$\gamma_0 \leftarrow$ apply detector and fetch feature, box pair from χ_{test}
$\gamma \leftarrow$ repeat γ_0 10 times
$\partial_T \leftarrow$ forward pass χ_{sample} and γ to the model ρ and perform 10 training iterations
repeat
    `/* bounding box prediction stage */`
    $y^{tc} \in \mathbb{R}^2 \leftarrow$ Perform convolution on $\delta(v_q) * \partial_T$
    $y^{bb} \in \mathbb{R}^4, p_q \leftarrow$ Regress candidate boundinng boxes and choose one with the highest confidence score.
    plot y^{bb} in the frame v_q
    `/* model update step */`
    if $p_q > \varepsilon$ **then**
        `/* append frame (+) to memory */`
        $\chi_{sample} \leftarrow \chi_{sample} + \delta(v_q)$
        $\gamma_t \leftarrow$ feature, box pair for v_q
        $\gamma \leftarrow \gamma - \gamma_t$
    end
    if $length(\chi_{sample}) > 50$ **then**
        `/* remove frame (-) from memory */`
        $\chi_{sample} \leftarrow \chi_{sample} - v_0$
        $\gamma \leftarrow \gamma + \gamma_0$
    end
    if 30 *new frames are appended* **then**
        $\partial_T \leftarrow$ forward pass χ_{sample} and γ to the model ρ and perform 1 training iteration
    end
until *Until novel* v_q *without bounding boxes is received*

Experimental Evaluation

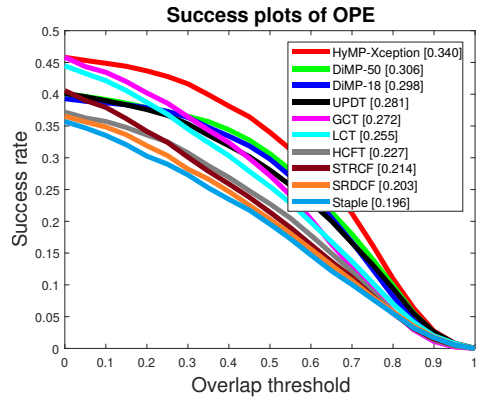
Table: Comparison of algorithms' AUC on the benchmark datasets. For VOT2018, we compared EAO score [KLM+18]. HyMP-X is HyMP with Xception [Cho17] as backbone feature extractor

Tracker	VOT-2018	OTB100	UAV123	UAV20L	DTB70	UUCT
Correlation Filter Trackers						
Staple [BVG+16]	16.9	58.6	45.0	33.1	35.1	19.6
SRDCF [DHSKF15]	11.9	59.8	46.4	34.3	36.3	20.3
STRCF [LTZ+18]	14.3	64.1	48.1	35.4	40.7	20.3
Tracekrs applied Correlation Filter on deeply learned features						
HCFT [MHYY18b]	19.9	64.7	48.6	36.8	41.5	22.7
LCT [MHYY18a]	22.1	65.2	49.4	35.9	43.1	25.5
Tracekrs exploited end-to-end deep learning pipeline						
GCT [GZX19]	27.6	64.8	50.8	46.1	44.2	27.2
UPDT [BJD+18]	38.3	**70.2**	54.5	49.5	45.7	28.1
DiMP-18 [BDGT19]	40.2	66	64.3	51.7	46.9	29.8
DiMP-50 [BDGT19]	43.1	68.4	65.4	52.8	47.5	30.6
End-to-end HyMP Tracker (ours)						
HyMP-18	40.1	66.8	66.2	52.5	47.1	31.7
HyMP-50	42.8	69.1	67.6	52.9	48.6	32.9
HyMP-X	**43.6**	69.4	**68.2**	**53.7**	**49.2**	**34.0**

Algorithm Performance Visualization on UUCT Dataset

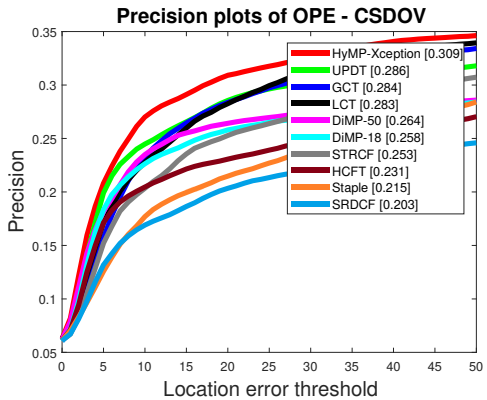


(a) Precision



(b) Overlap Success

Figure: Overall benchmark of SOTA trackers on UUCT



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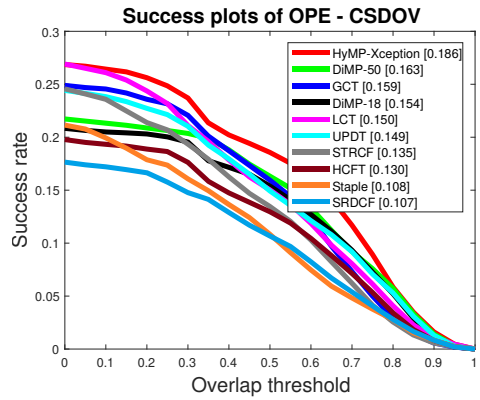

(b) Overlap Success

Figure: Benchmark on Crowd Split and Dispersed Out of View (CSDOV)

Thank You!

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