HELMHOLTZ AI | ARTIFICIAL INTELLIGENCE COOPERATION UNIT

Learning Fluid Flow Visualizations from In-Flight Images with Tufts

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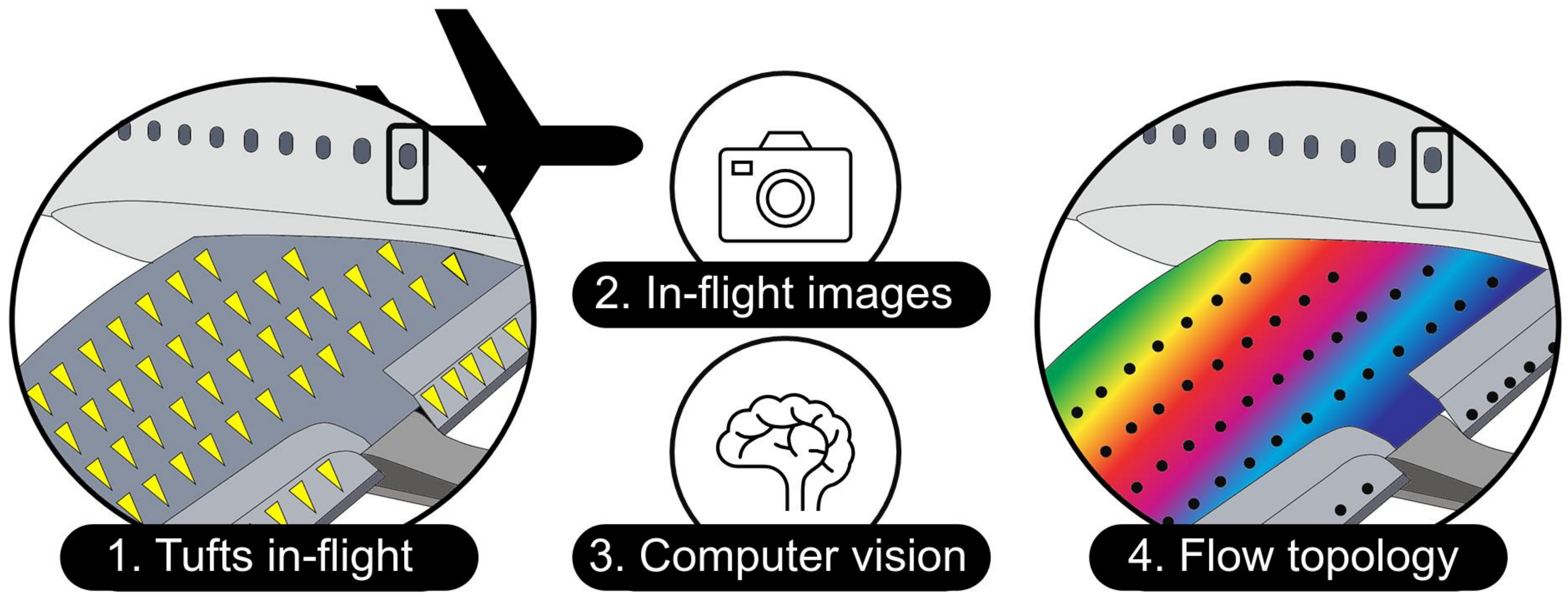
DLR

Main Idea

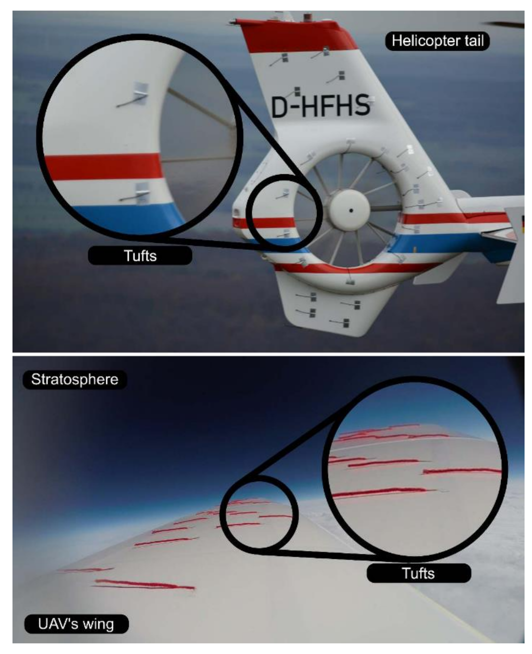


Problem: Not all fluid flow phenomena can be adequately represented In wind-tunnels or computational fluid dynamics.

Tufts are widely used experimentation method to visualize fluid flows during real test flights.

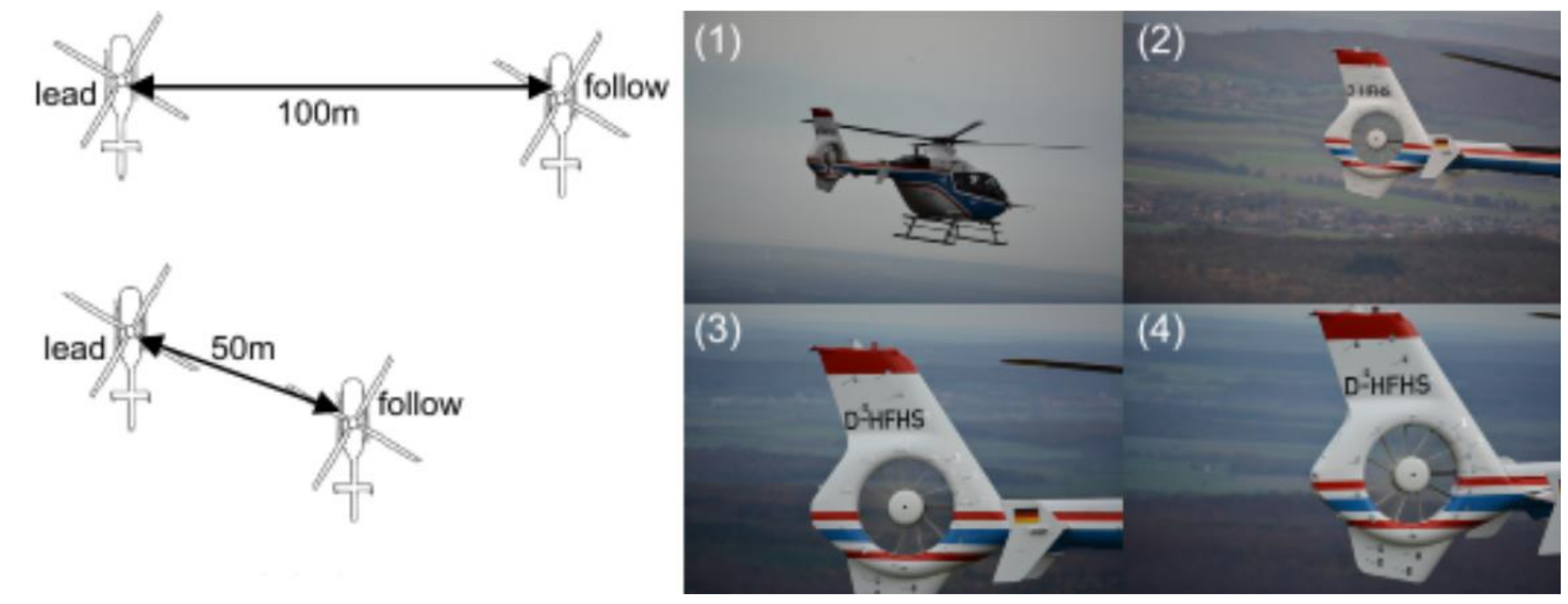
Main idea is to use deep learning methods to automatically segment the tufts.

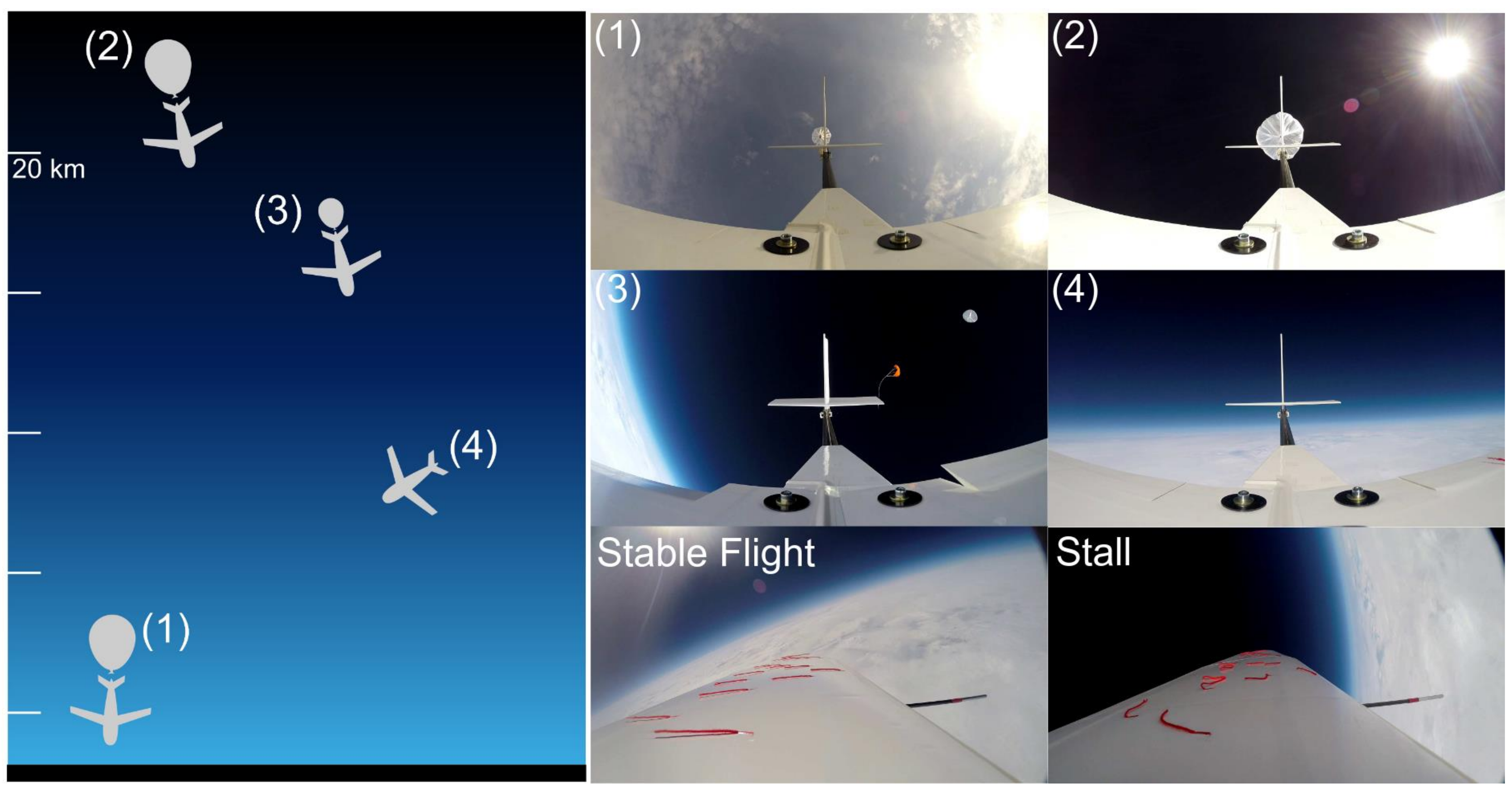
-> quantitative results can be obtained!
-> many images can be analysed!



Methods

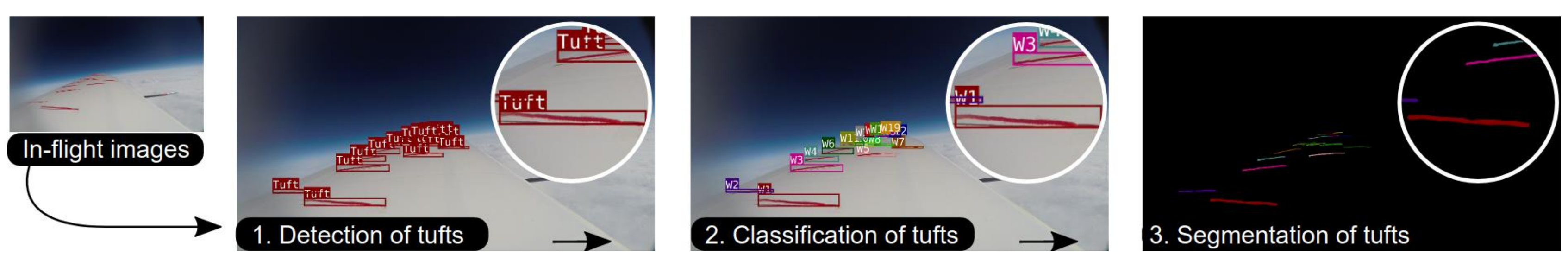
(1) Data Collection (e.g., helicopter flight within DLR)





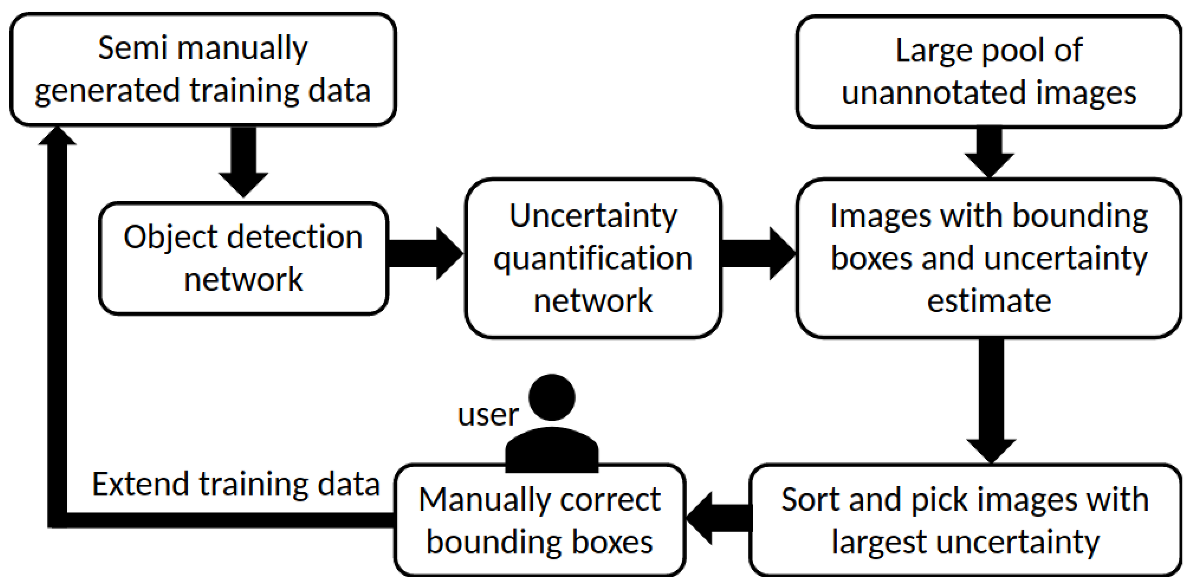
(2) Challenges and A Probabilistic Solution

- Segmentation of objects with similar appearance but different labels.
- No availability of the segmented segmentation masks.
- Real-world challenges, like appearance change, lighting, etc.



Divide the problem into smaller problems of detection, classification, and then instance segmentation!

- Object Detection with Active Learning



A pool-based active learning with coarsely annotated pool data. The initial coarse annotations are generated manually with the aid of feature-based image matching.

- Label Propagation with Uncertainty

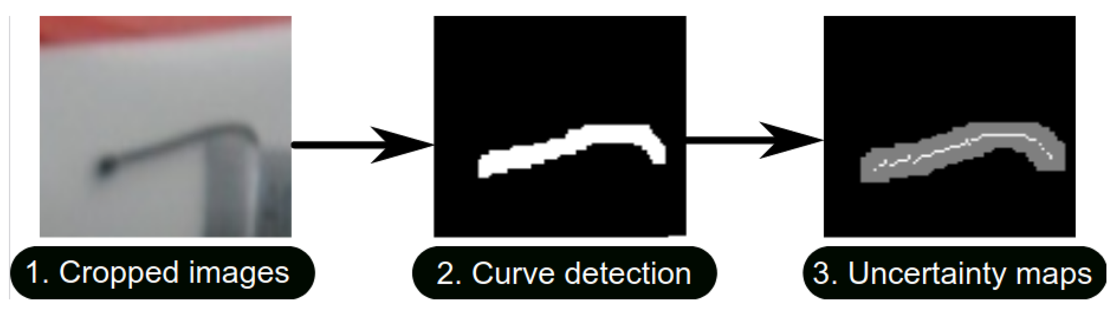
Algorithm 1: Tuft Classification Algorithm with Uncertainty Driven Label Propagation

input :
I_T The current test image from a video stream.
$p(y^* \mid x^*, \mathcal{D}), b$ Outputs of probabilistic object detection. $x^* = I_T$ and $b \leftarrow \mathbb{E}[p(y^* \mid x^*, \mathcal{D})]$
$\{I_{S,i}\}_{i=1}^{K}$ The key-frames: a set of source images with annotations.
L The total number of tufts on an aerodynamic vehicle.

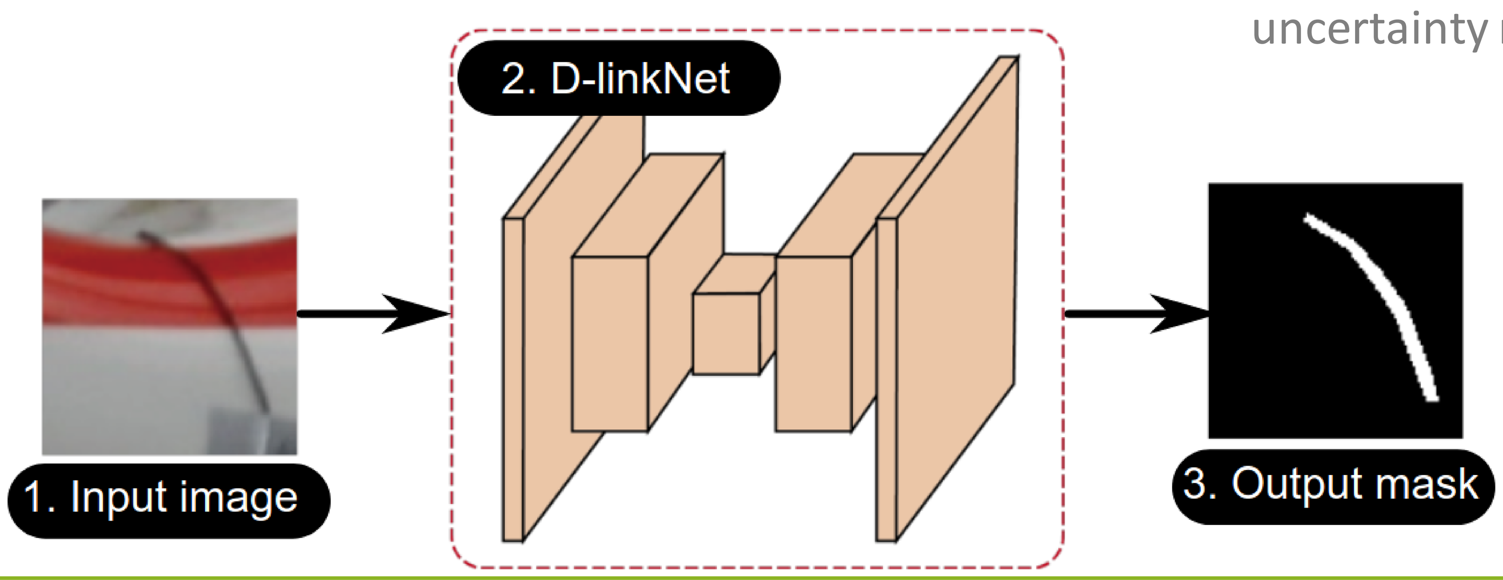
output:
$\{c_j\}_{j=1}^{L}$ The class labels for each bounding boxes.
$\{I_{T,i}\}_{i=1}^{K+1}$ New key-frames after evaluating results on the current image I_T.

begin
  /* Key-frame based Image matching */
  for all the K images in the key-frames **do**
    $T_i, C_i \leftarrow$ image_matching($I_{S,i}, I_T$) $\forall i$; // Image matching; Results in transformations T_i and costs C_i
  end
  $T \leftarrow \arg\min(\{C_i\}_{i=1}^{K})$; // Select the result with the least cost
  $\{c_j\}_{j=1}^{L} \leftarrow$ label_propagation(b, T) ; // Label all L bounding boxes using Hungarian algorithm
  /* Is the results reliable? Multi-criteria decisions (MCD): */
  /* 1. If all L tufts detected (binary threshold) */
  /* 2. If the confidence is high (pre-set threshold) */
  /* 3. If the matching costs are low (pre-set threshold) */
  RS $\leftarrow$ MCD($p(y^* \mid x^*, \mathcal{D})$, C_i, L) ; // Evaluate the Reliability Score (RS)
  if *RS is True* **then**
    $\{I_{T,i}\}_{i=1}^{K+1} \leftarrow$ update_keyframe($\{I_{S,i}\}_{i=1}^{K}$, I_T, $\{c_j\}_{j=1}^{L}$, b) ; // Update if reliable more than a threshold
end

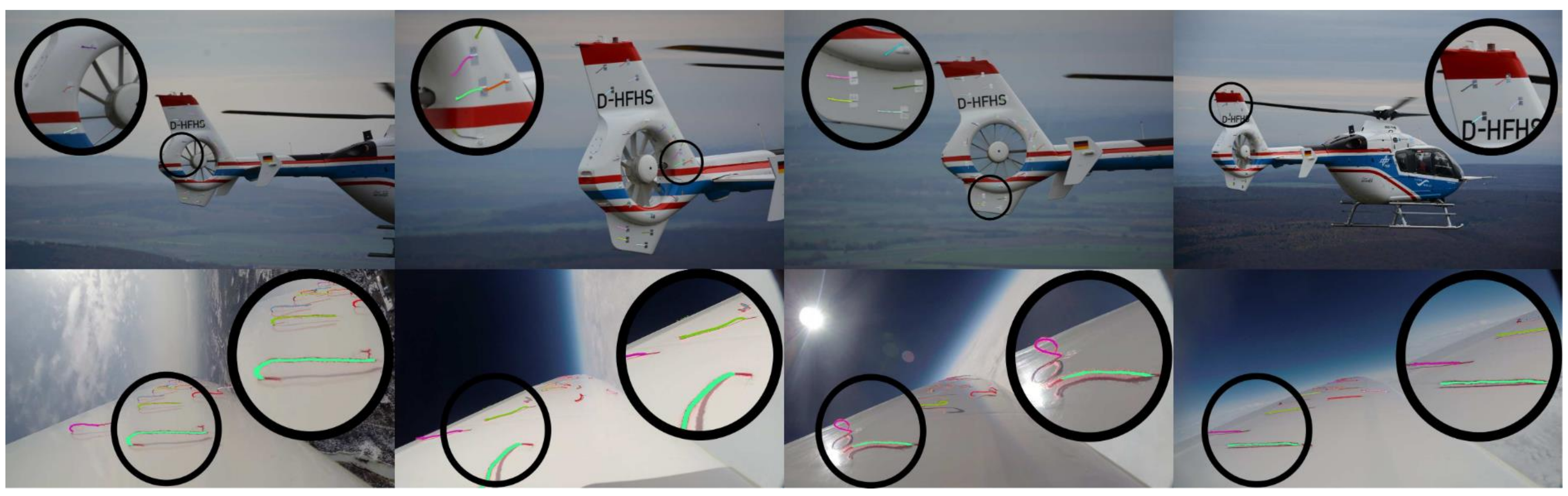
- Weakly Supervised Segmentation



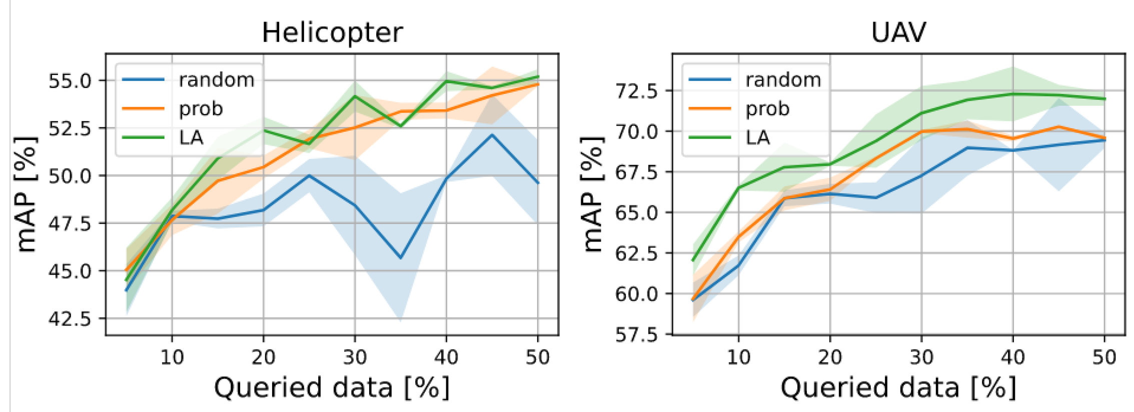
Generation of annotations for segmentation. A classical curve detection is combined with uncertainty masks.



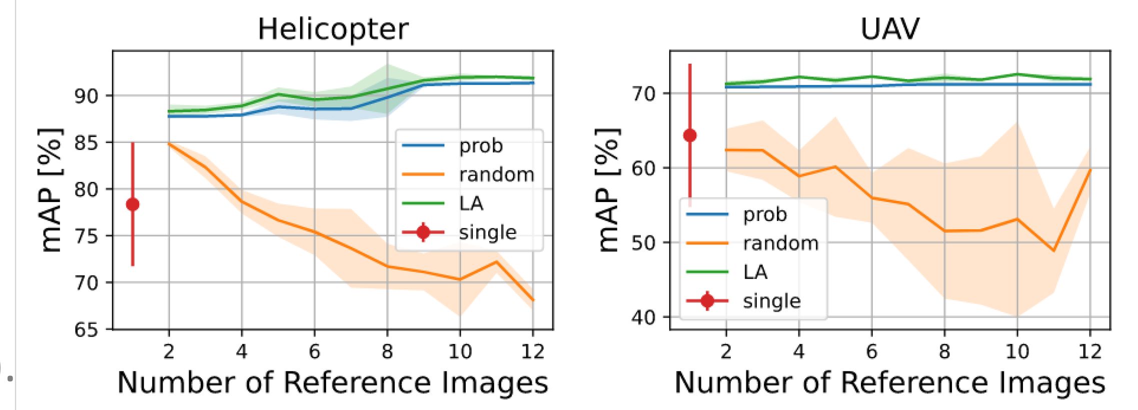
Results



- Semantic segmentation without manual annotations of segmentation masks.
- Probabilistic approaches for the real world applications (manned helicopter and stratospheric UAV flights).



Uncertainty-based active learning -> saves annotations



Uncertainty-based label propagation-> saves annotations