

HENSOLDT Analytics

Generating Robust Motion Maps to Enhance Object
Detector Performance

Sébastien Grand

Supervisor: Dr. Jonathan Kobold

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ModIA - Enseeiht

Table of contents

- Introduction
- Motion Detection
- Object Detection
- Possible Improvements
- Conclusion

Introduction

- Context & Objectives
- Previous Work
- Requirements & Literature Review

Context & Objectives

Do you see any object on this frame ?



Figure 1 : Frame from Analytics drone dataset

Context & Objectives

Would you have seen the drone on this frame if it did not have a bounding box?

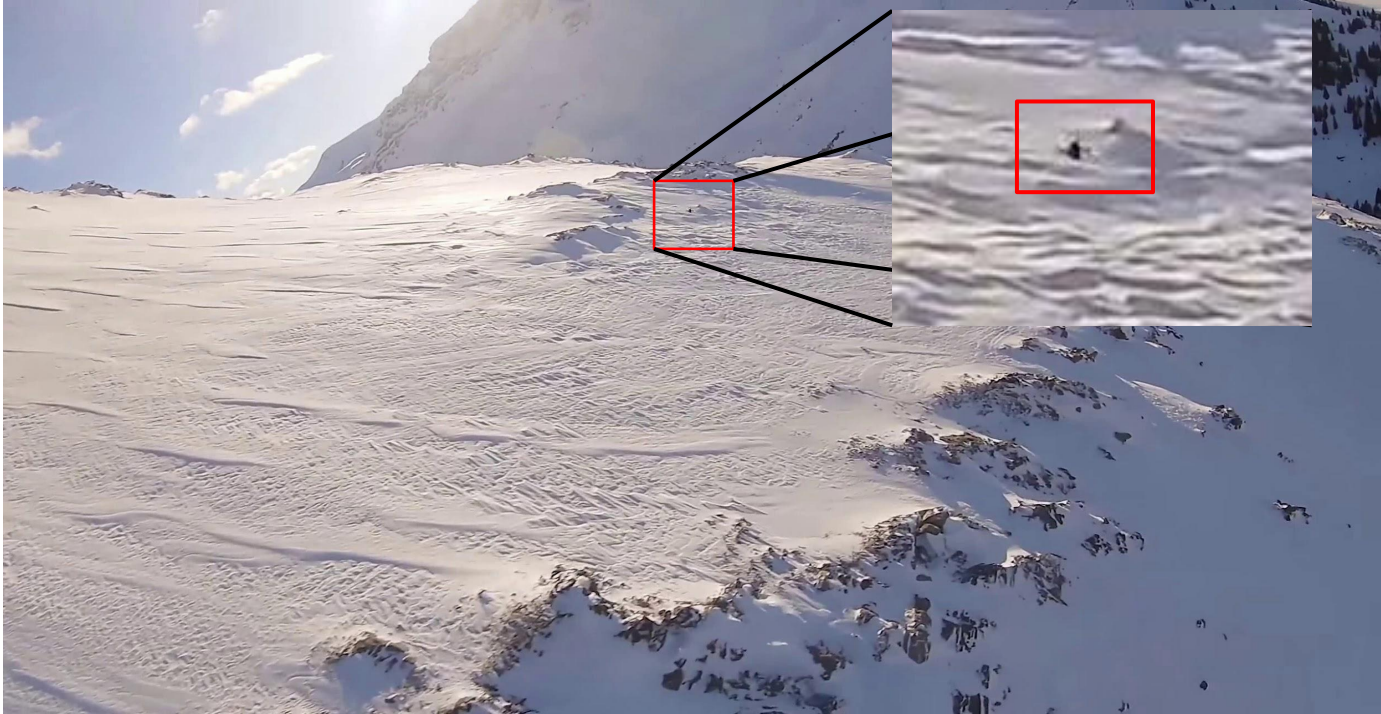


Figure 2 : Frame from Analytics drone dataset

Previous Work

For *visibility*, the video from the *Davis* dataset [1] called *BMX-bumps* is used as an example of *motion detection*.



Figure 3 : 10th frame from BMX-bumps video

Motion Detection
Model



Figure 4 : Frame-difference computed with 2 frames



Figure 5 : Frame-difference computed with 3 frames [2]

Requirements & Literature Review

- List of Requirements:

- The method must be executable on the *CPU* :
 - No research on *Deep Learning* methods.
- The method should handle various situations :
 - Moving Camera;
 - Low-contrast;
 - Dynamic Background;
 - Tiny Objects

- Literature Review:

- Optical Flow;
- Panorama creation;
- Subspace Learning;

Motion Detection : PRPCA

- Video Registration : Panorama Creation
- Motion Detection : Robust PCA Formulation
- Motion Detection : Decomposition Results
- Post-processing : Object Detection
- Results & Discussions

Video Registration : Frames 1

My camera captures a first frame.



Figure 6 : 1st frame from BMX-bumps video

Video Registration : Frames 2

My camera captures a second frame.



Figure 7 : 2nd frame from BMX-bumps video

Video Registration : Frames 3

My camera captures a third frame.



Figure 8 : 3rd frame from BMX-bumps video

Video Registration : Panorama of 3 frames

It is possible to align all the frames together with respect to a point of view reference.



Figure 9 : 3rd frame from BMX-bumps video

Video Registration : Panorama Creation

Video Registration procedure as proposed in [3].



Figure 10 : Batch of N frames

Feature Extraction
→
Matching Features



Figure 11: Feature Extraction & Matching

Homographies
Estimation

$$\begin{pmatrix} \mathcal{H}_{2 \rightarrow 1} \\ \vdots \\ \mathcal{H}_{\text{anchor} \rightarrow k} \\ \vdots \\ \mathcal{H}_{N-1 \rightarrow N} \end{pmatrix}$$

Frame Alignment
using the Homographies



Figure 12: Registered frames



Figure 13: Support of the Registered frames

Video Registration : Resulting Panorama

With a batch of 20 frames captured by moving camera, it is possible to obtain this panorama :



Figure 14: Resulting panorama made of 20 frames
with the 10th frame as reference

Motion Detection : Separating the Motion from the Background

How can we separate what is moving (the bike) from what is static (the background) ?



a) Original RGB frame

=



b) Background

+



c) Motion Detected

Figure 15: Foreground/Background Segmentation

Motion Detection : Separating Motion from the Background

Problem formulation :

- Registered frames are stored in X as :

$$X = [\text{vec}(\tilde{x}_1), \dots, \text{vec}(\tilde{x}_p)]$$

- where, $\text{vec}(\cdot)$ is the function to vectorize a frame;
- where \tilde{x}_k refers to the k -th registered frame of X with respect to the *anchor frame*.
- Then, X can be decomposed [4] as :

$$\begin{aligned} \min_{L, S} \quad & ||L||_* + \lambda ||S||_1 \\ \text{subject to} \quad & \mathcal{P}_M(L + S) = \mathcal{P}_M(X) \end{aligned}$$

Motion Detection : Resulting Decomposition

Decomposition of *Paragliding* video from *Davis* dataset :



Figure 16: Paragliding Foreground/Background Segmentation

Decomposition of drone video from Analytics dataset :



Figure 17: Foreground/Background Segmentation of Drone video from Analytics Dataset

Post-processing : Object Detection Input Creation

Creation of *Binary Motion Map* & *Trajectory Map* :



Figure 18: RGB frame

Motion Detection with RPCA



Figure 19: Raw Motion Map

Otsu [5] Thresholding

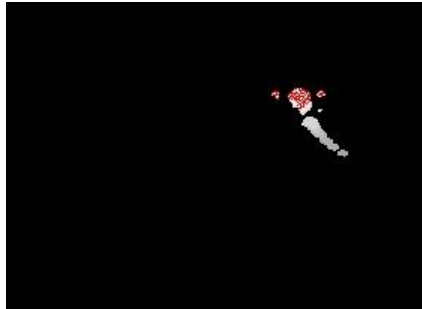


Figure 20: Trajectory Map

Binary Motion Map
Accumulation

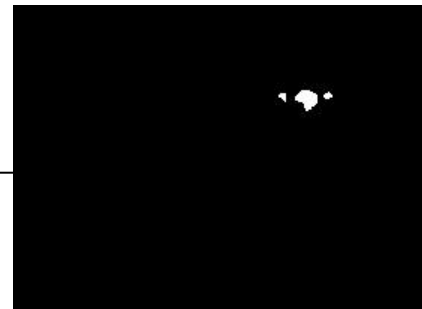


Figure 21: Binary Motion Map

Results : Datasets & Metrics

- The two datasets used for *evaluation* are :
 - *Davis Challenge* dataset :
 - Dataset for *Background/Foreground Separation*;
 - The filming *camera is moving*;
 - *ChangeDetection.net* [6] dataset :
 - Database for testing *change detection* algorithm;
 - The filming camera jitters or the background is dynamic;



Figure 22: Motion Detection Result on BMX video

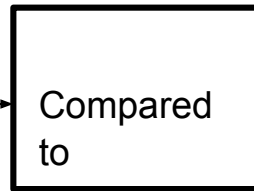


Figure 23: Ground Truth of BMX-bumps segmentation

Results : Results & Discussions

Results of the experiments conducted on the Davis and CDnet datasets:

Video informations				PRPCA			Baseline
Dataset	Sequence	Camera	Frames	Precision	Recall	F-measure	F-measure
Davis 2017	bmx-bumps	moving	40	0.78	0.72	0.75	0.53
Davis 2017	tennis	moving	35	0.89	0.54	0.67	0.45
CDnet 2014	canoe	jittering	80	0.25	0.26	0.22	0.11
CDnet 2014	fall	jittering	80	0.80	0.53	0.61	0.22

Table 1: Results of PRPCA and baseline model on 4 different videos.

- True Positive (TP) : The model prediction matches the ground truth;
- False Positive (FP) : The model predicted a label that does not match the ground truth;
- False Negative (FN) : The model does not predict a label, but a ground truth label exists;
- Precision (P) : $TP / (TP + FP)$
- Recall (R) : $TP / (TP + FN)$
- F-measure/F1-score: $2 PR / (P + R)$

Object Detection

- Dataset for Object Detection
- Input Data for Object Detection
- Training Procedure
- Experiments & Results

Dataset for Object Detection

Slow Motion Camera Dataset

- Characteristics :
 - Easy motion compensation;
 - Tiny drones;
 - Low-contrast;
 - 13 videos;
 - ~50 frames / video;



Figure 24: Example of *RGB frame* and *Raw Motion Map* in *slow motion* dataset

Dataset for Object Detection

High Motion Camera Dataset

- Characteristics :
 - Difficult motion compensation;
 - More visible drones;
 - 11 videos;
 - ~50 frames / videos;



Figure 25: Example of *RGB frame* and *Raw Motion Map* in *high motion* dataset

Dataset for Object Detection

Slow & High Motion Camera Dataset

- Characteristics :
 - Various difficulty of motion compensation;
 - Various drone sizes;
 - Various image quality;

Input Data for Object Detection

The different *inputs* :

- *3-channel* input :

- RGB frame (Baseline)

- *4-channel* input :

- RGB frame + Raw Motion Map
- RGB frame + Binary Motion Map

- *6-channel* input :

- RGB frame + Trajectory Map

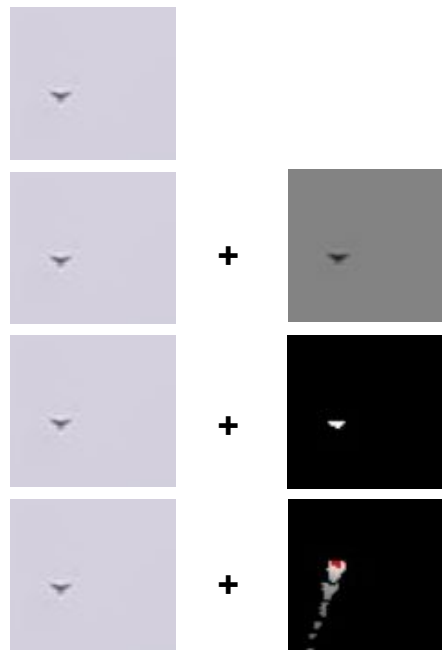
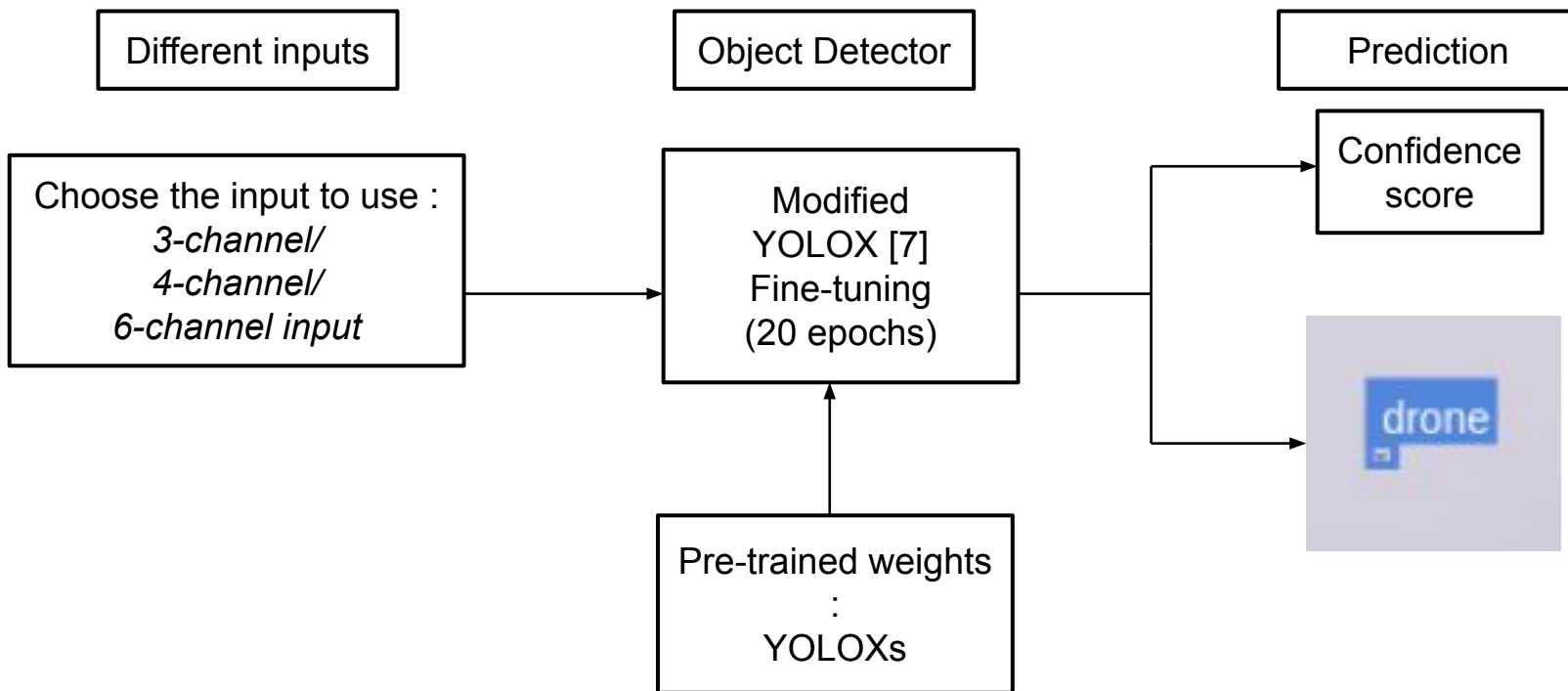


Figure 26: The different inputs for object detection experiments

Training Procedure



Experiments & Results

Results of the experiments conducted on the Drone datasets of Analytics:

Dataset	Input	$AP_{drone}(\%)$	$AR_{drone}(\%)$
Slow motion camera	RGB	49.7	53.2
	RGB - Raw motion	52.3	54.2
	RGB - Binary motion	58.4	62.0
	RGB - Trajectory	54.5	57.0
High motion camera	RGB	56.4	61.0
	RGB - Raw motion	55.7	58.0
	RGB - Binary motion	48.1	52.1
	RGB - Trajectory	52.2	54.0
Coupled dataset	RGB	45.6	49.8
	RGB - Raw motion	51.2	55.7
	RGB - Binary motion	49.7	52.0
	RGB - Trajectory	53.7	56.3

Table 2: YOLOX results on different datasets (Analytics)

AP (%) : average of all precision measurements for each detection.

AR (%) : average of all recall measurements for each detection.

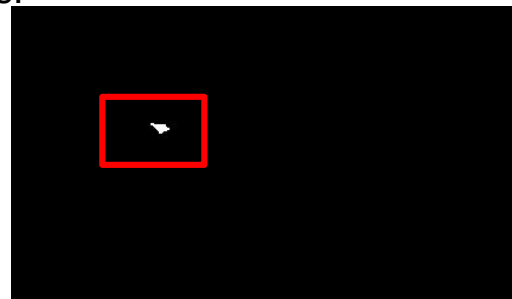


Figure 27: Accurate Motion Map (good ego-motion compensation)

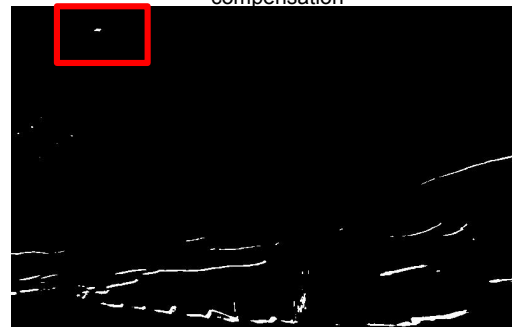


Figure 28: Noisy Motion Map due to high ego-motion

Possible Improvements & Future Work

- ◆ Future improvements :
 - Motion compensation :
 - Extract better features;
 - Estimate better Homographies;
 - Elimination of clutter (moving trees, flowing water):
 - CNN to train to remove clutter;

Conclusion

- In this work, I was able to :
- Learn and perform *motion compensation* by panorama building approach;
- Learn and perform *motion detection* with *Robust PCA*;
- *Improve motion detection* compared to previous work;
- Fine-tune an object detector with different inputs;
- Show that adding *relevant motion information* to an RGB image as input to an object detector *improves* its performance at detecting *small drones*.

Thanks for your attention.

Any questions ?

References

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- [6] Y. Wang, P.-M. Jodoin, F. Porikli, J. Konrad, Y. Benezeth, and P. Ishwar, “CDnet 2014: An expanded change detection benchmark dataset,”
- [7] Z. Ge, S. Liu, F. Wang, Z. Li, and J. Sun, “YOLOX: Exceeding YOLO series in 2021.”