Adaptive Birth for the Generalized Labeled Multi-Bernoulli (GLMB) Filter in Satellite Videos

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Overview

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Problem Statement

Multi Object Tracking (MOT) in Remote Sensing

Sample Remote Sensing Video

© WPAFB 2009

Dayton, OH, USA

> **MOT Objective:**
- Extract target states from measurements

> **Sample Applications:**
- Urban development
- Traffic estimation
- Commerce management
- Law enforcement
- Border security

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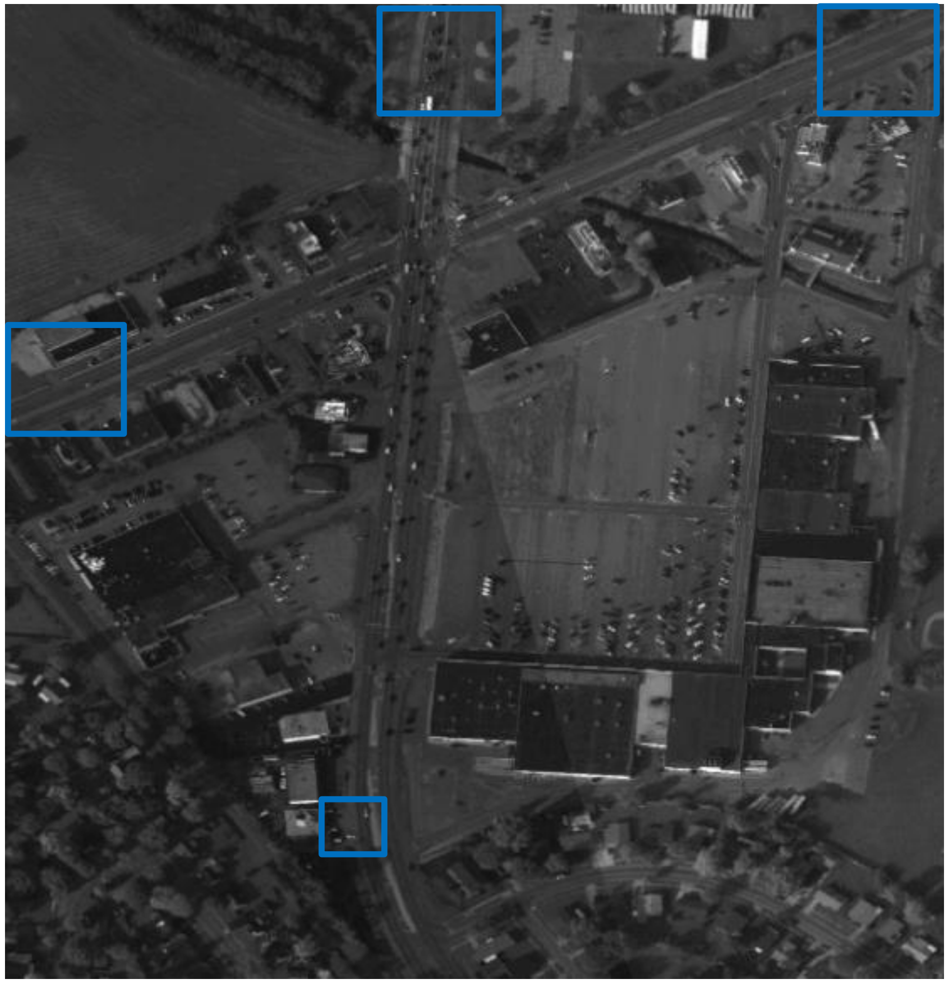
Challenges:

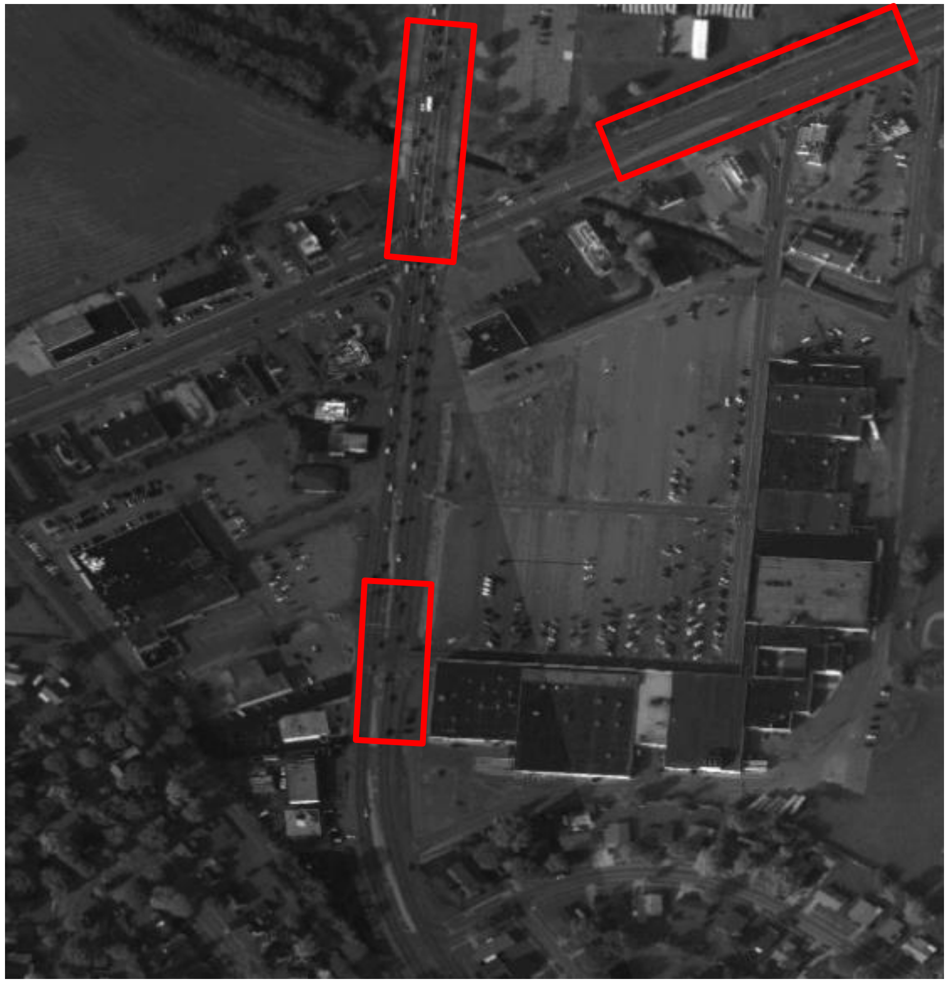
- **Varying number of targets:**
  > Targets may appear or disappear from:
    - Image borders
    - Parking lots and garages
    - Shadows and occlusions



Challenges:

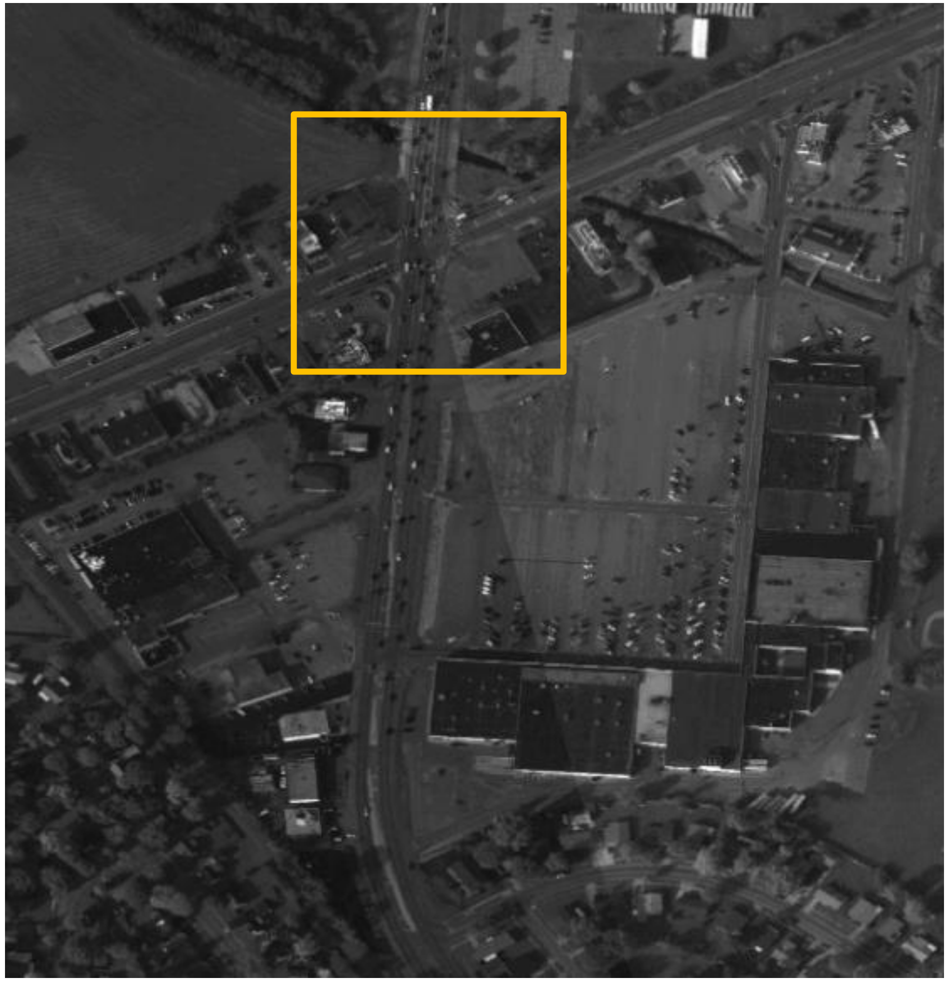
- **Varying number of targets**

- **Changing object dynamics**:
  > Objects may:
    - Move at very high speeds
    - Change directions rapidly
    - Stop at intersections



Challenges:

- **Varying number of targets**
- **Changing object dynamics**
- **Crowded scenes**:
  - > Objects can be separated a few pixels from each other



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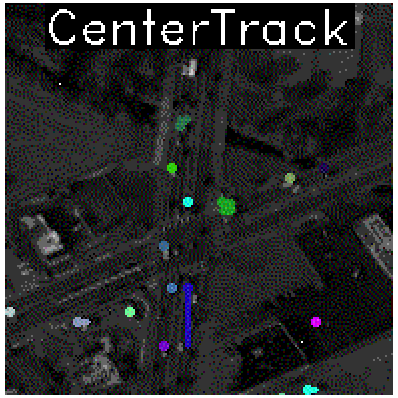
Popular Tracking Frameworks

Popular Tracking Frameworks

Deep Learning: CenterTrack [Zhou, 2020]

- ✓ Joint detection-tracking
- ✓ Regresses velocity vector
- x Recover tracks with ad-hoc frameworks
- x Requires 2D + time labels



Center Track [Zhou, 2020]

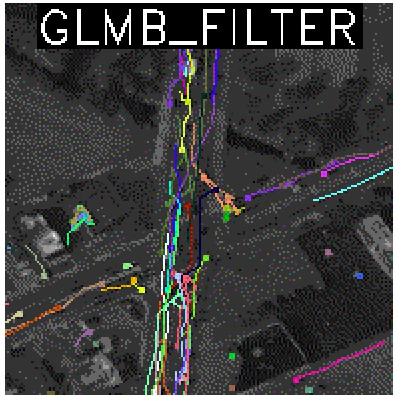
Real time:
SORT [Bewley, 2016] & DeepSORT [Wojke, 2017]

- ✓ Achieves competitive results with real-time performance
- x Relies on ad-hoc data association methods
- x DeepSORT relies on large object features

Sort [Bewly, 2016]

Random Finite Sets (RFSs):
PHD filter [Vo, 2004] and GLMB filter [Vo, 2014]

- ✓ Bayesian multi-object formulation
- ✓ Robust to clutter and misdetections
- x Requires of approximations to remain computationally feasible



GLMB [Vo, 2014]

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The GLMB Filter

Random Finite Sets (RFS) Framework

Measurements and objects' states are modeled with RFSs [Mahler, 1994]:

Measurement Set Modeling

Single measurement: $\mathrm{z_i} = [p_i]^T$

Frame multi-measurement set: $\boldsymbol{z_k} = \{z_1^k, z_2^k, \dots, z_{M_k}^k\}$

Sequence measurement set: $Z_k = \{\boldsymbol{z_1}, \boldsymbol{z_2}, \dots, \boldsymbol{z_k}\}$

Target Set Modeling

Single object state: $\mathrm{x_j} = [p_j, v_j, w_j, h_j]^T$

Frame multi-object set: $\boldsymbol{x_k} = \{x_1^k, x_2^k, \dots, x_{N_k}^k\}$

Sequence state set: $X_k = \{\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_k}\}$

Prediction (prior):

$$p(X_k|Z_{1:k-1}) = \int p(X_k|X_{k\,-1})\; p(X_{k-1}|Z_{1:k-1})\, \delta x_{k-1}$$

Update (posterior):

$$p(X_k|Z_{1:k}) = \frac{p(Z_{1:k}|\,X_k)p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})}$$

k: Time index
p: position
v: velocity
a: acceleration
N_k: number of objects
M_k: number of measurements

Labelled RFSs and the GLMB Filter

Labelled targets are modelled with Labelled multi-Bernoulli distributions

Target Set Modeling

Single object state: $\mathrm{x_j} = \left[p_j, v_j, w_j, h_j\right]^T$

Frame multi-object set: $\boldsymbol{x_k} = \left\{x_1^k, x_2^k, \dots, x_{N_k}^k\right\}$

Sequence state set: $X_k = \{\boldsymbol{x_1}, \boldsymbol{x_2}, \dots, \boldsymbol{x_k}\}$

Prediction (prior):

$$p(X_k|Z_{1:k-1}) = \int p(X_k|X_{k-1})\ p(X_{k-1}|Z_{1:k-1})\ \delta x_{k-1}$$

Update (posterior):

$$p(X_k|Z_{1:k}) = \frac{p(Z_{1:k}|\ X_k)p(X_k|Z_{1:k-1})}{p(Z_k|Z_{1:k-1})}$$

k: Time index
p: position
v: velocity
a: acceleration
N_k: number of objects
M_k: number of measurements

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Proposed Adaptive Birth

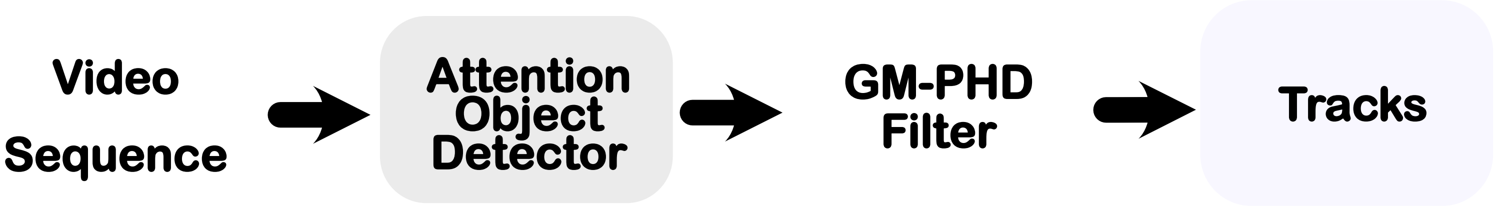
Learning a Velocity History Map h_v^k

$$
\boldsymbol{h_v^k(\hat{p}_i)} = \begin{cases} \dfrac{\boldsymbol{h_v^{k-1}(\hat{p}_i) + \hat{v}_i}}{\mathbf{2}} & \boldsymbol{if\ \left\| h_v^{k-1}(\hat{p}_i) \right\| \neq 0} \\ \boldsymbol{\hat{v}_i} & \boldsymbol{if\ \left\| h_v^{k-1}(\hat{p}_i) \right\| = 0} \end{cases}
$$

GLMB Filter with Adaptive Birth

Object Detection: Patch-based CNN

Object Tracking: GM-PHD Filter



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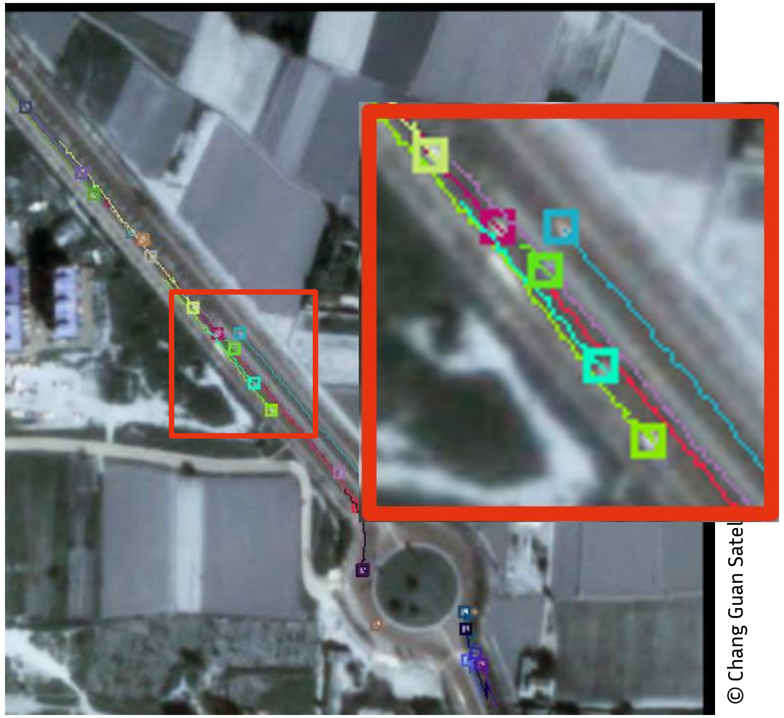
Results

Sample Area 1

Jilin-1 Satellite Constellation. Resolution: 1.0 m, Frequency: 20 Hz

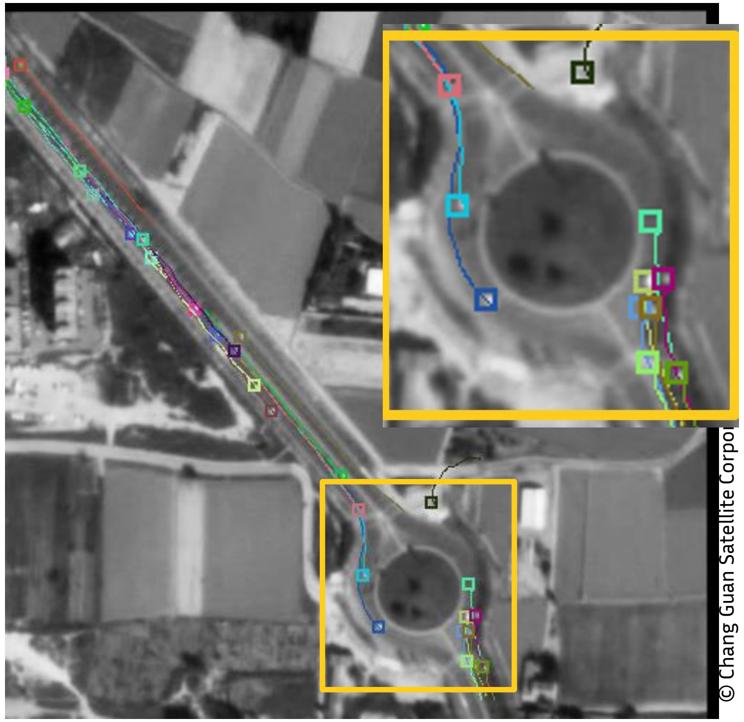
Ground Truth



Filter Output

Sample Area 1

Jilin-1 Satellite Constellation. Resolution: 1.0 m, Frequency: 20 Hz

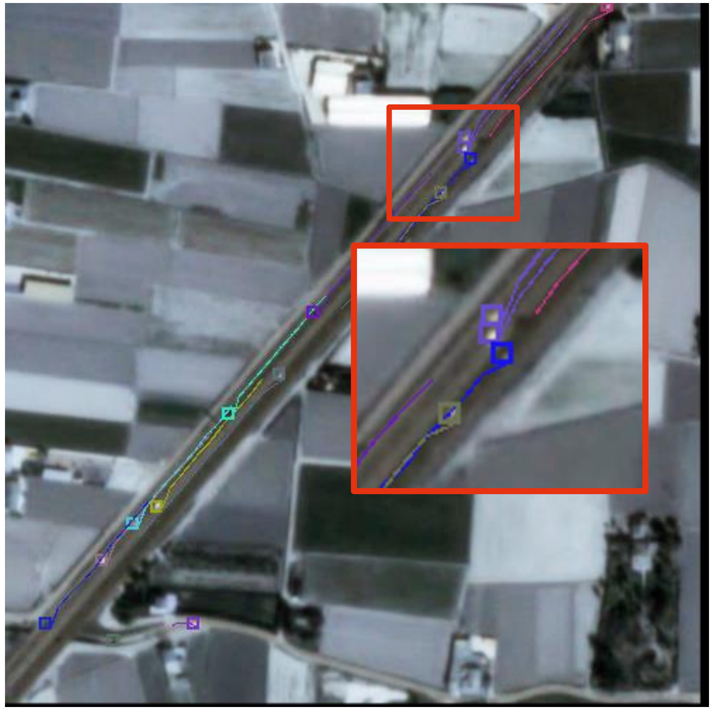


Ground Truth

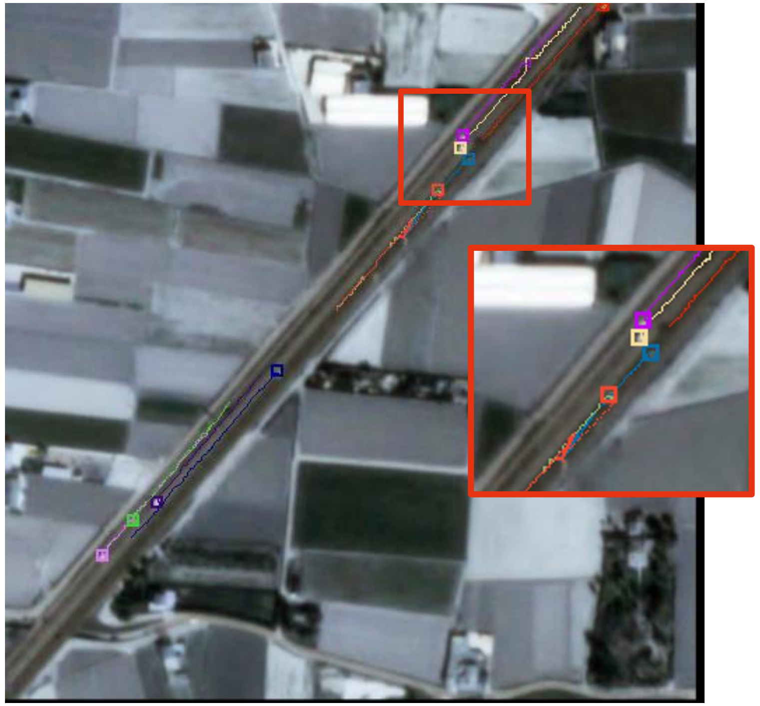
Filter Output

Sample Area 2

Jilin-1 Satellite Constellation. Resolution: 1.0 m, Frequency: 20 Hz



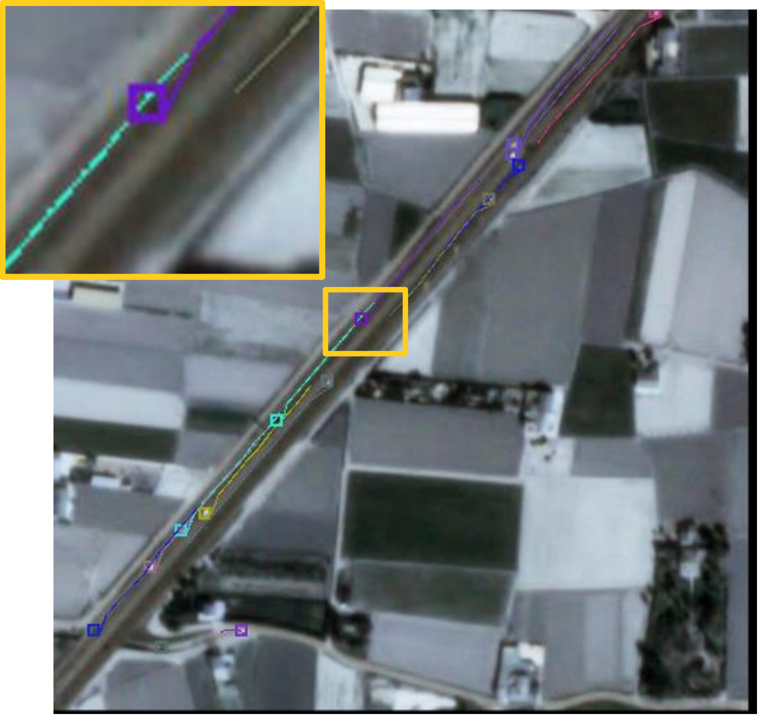
Ground Truth



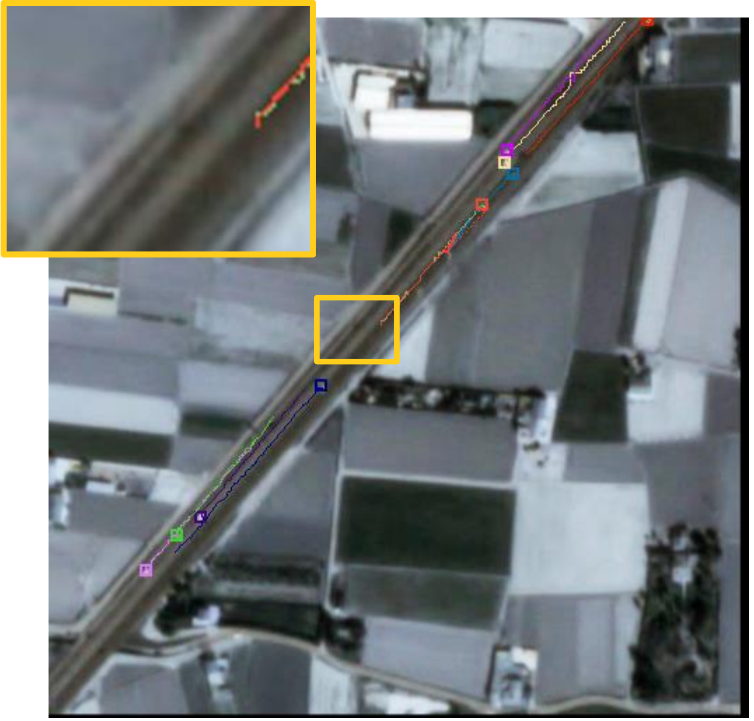
Filter Output

Sample Area 2

Jilin-1 Satellite Constellation. Resolution: 1.0 m, Frequency: 20 Hz



Ground Truth



Filter Output

ClearMOT [Bernarin, 2008] Scores

FN: False negative
FP: False positive
GT: GT objects
IDS: identity switch

d_i^k: distance to GT
N_{Frames}: number of frames
M_k: number of detected objects

MOTA: Multiple Object Tracking Accuracy

- Ranges from $(-\infty, 100]$
- Function of true positives, false positives, identity switches

$$MOTA = 1 - \frac{\sum_{k=1}^{N_{Frames}} FN_k + FP_k + IDS_k}{\sum_k GT_k}$$

MOTP: Multiple Object Tracking Precision

- Ranges from $[0.0, \infty)$
- Function of distance between detections-ground truth

$$MOTP = \frac{\sum_{k=1}^{N_{Frames}} \sum_{i=1}^{N_k} d_i^k}{\sum_k M_k}$$

Average Scores for AoIs 2, 34, 42

Method	MOTA	MOTP
Proposed	**0.871**	**0.523**
GLMB [Vo, 2017]	0.742	0.547
T-GMPHD [Aguilar, 2021]	0.464	0.554
SORT [Bewley, 2016]	0.478	0.824

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Conclusion

Conclusion

We presented a track by detection approach to track tiny moving objects by using an attention driven CNN inference and the GM-PHD filter.

- The **patch selection mechanism** contributed to **reduce false positives** and to perform training and inference with a CNN.
- The GM-PHD filter performs a **direct multi-object approach** in comparison to common techniques of using several independent Kalman filters.
- We obtain **both better detection and tracking** scores than competing methods

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Thank you!
Merci !
Gracias!