# OBJECT GEOLOCATION USING MRF BASED MULTI-SENSOR FUSION

*Vladimir A. Krylov* and Rozenn Dahyot
ADAPT Centre, School of Computer Science & Statistics, Trinity College Dublin, Ireland

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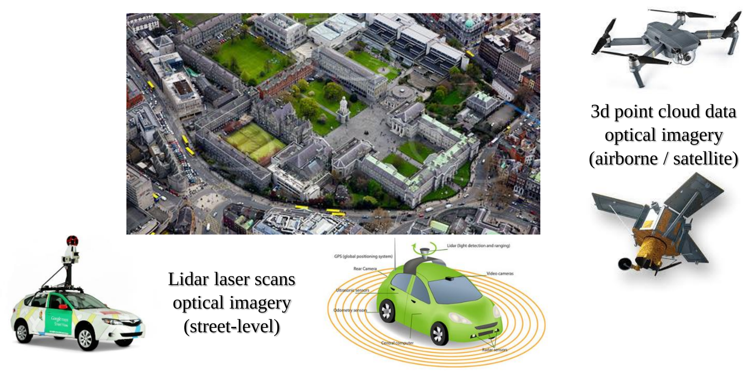
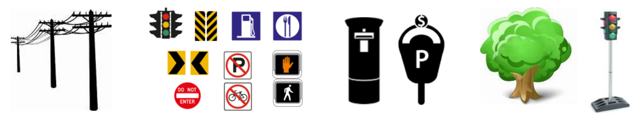
## Objectives

- Automatic complex scenes analysis: multiple objects.
- Recycling abundant existing image datasets.
- Efficient detail-preserving fusion of multi-sensor data.




- We design a multi-sensor fusion pipeline that can perform discovery and geolocation of objects across various imaging and sensory modalities.
- In this work we study the case of two modalities: **Street Level Imagery** and **LiDAR.**
- We consider detection of compact stationary objects:



## Image Processing

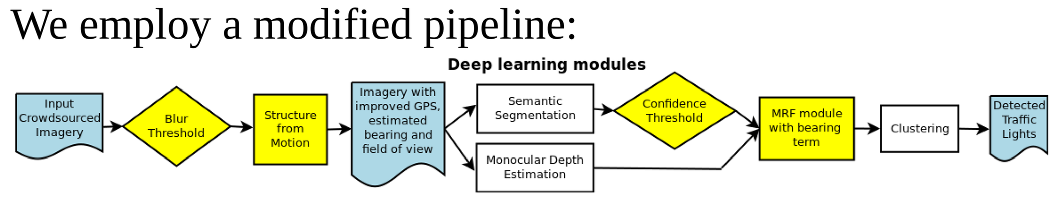
- **Assumptions**:
  - Street level imagery is the primary source.
  - Object sparsity: 1m apart.
- **Street Level Imagery**: We perform
  - ✓ Semantic Segmentation
  - ✓ Monocular depth estimation

  via state-of-the-art fully CNN models.
  These are finetuned on *Cityscapes* and *Mapillary Vistas* street level imagery datasets.
- **LiDAR data**: We obtain
  - ✓ Candidate point extraction

  via template matching.

## Crowdsourced Imagery

In [3] we use crowdsourced *Mapillary* images for object discovery and geolocation.
We employ a modified pipeline:




We rely on *Laplacian filtering* for thresholding and *Structure from Motion* to estimate bearing, adjust GPS.

**Conclusions**:

- Requires more data to achieve comparable recall;
- Reduced position estimation accuracy.

## Multi-Sensor Fusion Pipeline

- We perform optimization for object discovery and geolocation based on the following input estimates:
  - ✓ Individual discovered objects (semantic segmentation)
  - ✓ Monocular depth estimated for each discovered object $\Delta_i$
  - ✓ LiDAR candidate matches

- We define a **Markov Random Field** (MRF) model over the space $X$ of all view-rays intersections:
  - label $z=0$ if not occupied by object
  - label $z=1$ if occupied
- MRF configuration is characterized by its corresponding energy $U$. *Optimal = minimum of U.* Optimization: *ICM*.

**Energy terms**:

$\Delta$ – depth estimates
$d$ – triangulated distances
$L$ – distance to LiDAR match
$R_i$ - subset of $X$ on the same ray with $x_i$

- Unary consistency terms:

$$u_D(z_i|\mathcal{X},\mathcal{Z}) = z_i \sum_{j=1,2} \|\Delta_{ij} - d_{ij}\|^2$$

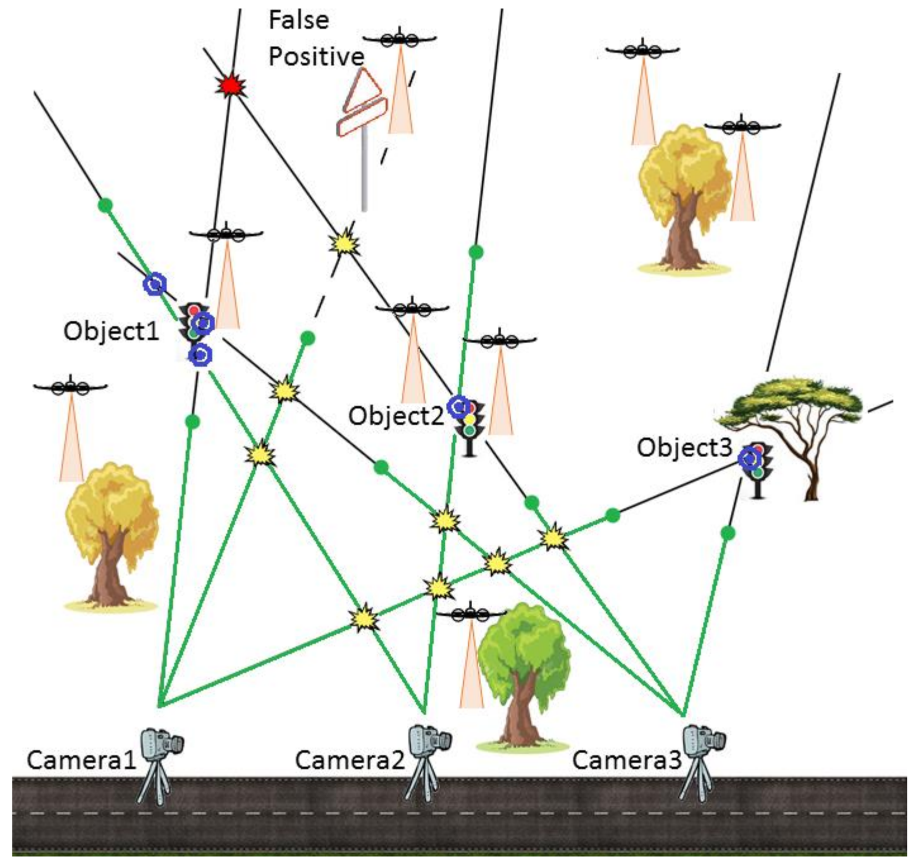
$$u_L(z_i|\mathcal{X},\mathcal{Z}) = z_i L_i^2$$

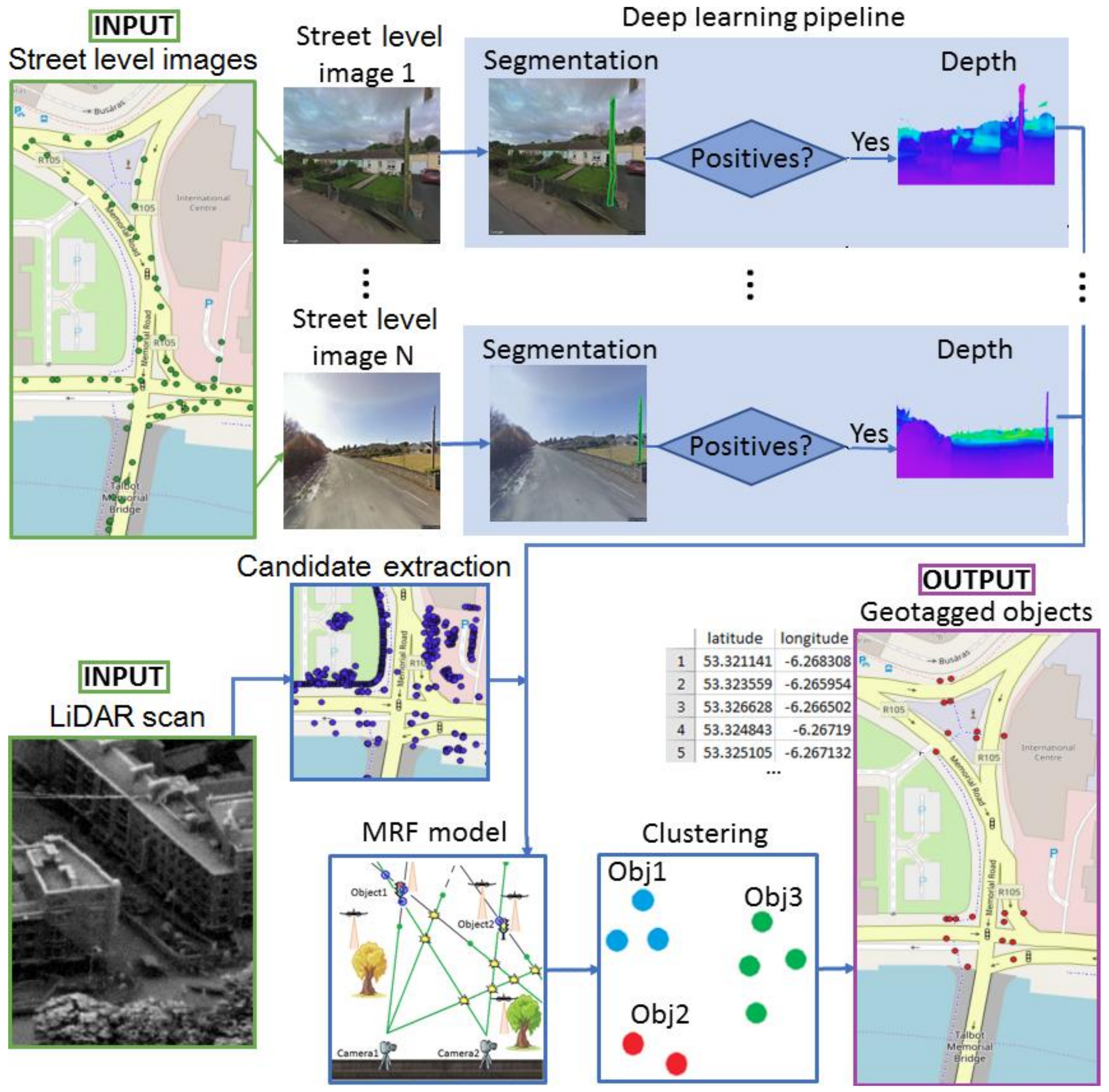
- Pairwise term. *No occlusions. No spread.*

$$u_0(R_i|\mathcal{X},\mathcal{Z}) = \prod_{x_n \in R_i} (1 - z_n)$$

- High-order term. *Penalize not matched rays.*

$$u_C(R_i|\mathcal{X},\mathcal{Z}) = \sum_{x_m, x_n \in R_i} z_m z_n \|x_m - x_n\|^2$$



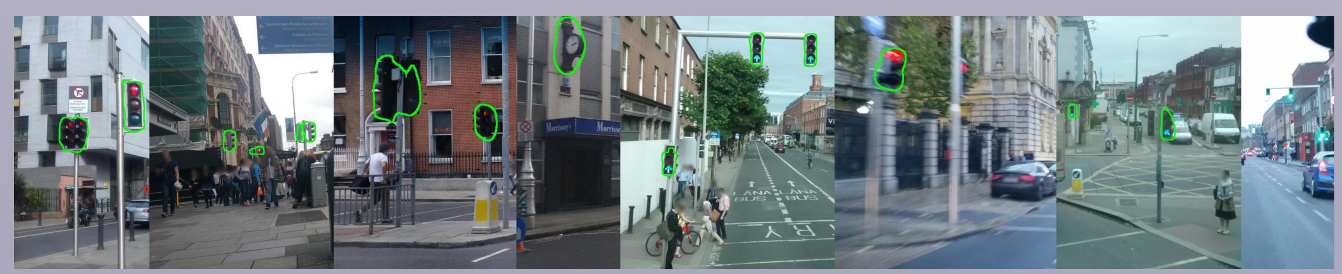




**Total energy**:

$$\mathcal{U}(\mathbf{z}) = \sum_{\forall x_i \in \mathcal{X}} \left[ c_D\, u_D(z_i) + c_L\, u_L(z_i) \right] + \sum_{\forall \text{ rays } R_j} \left[ c_C\, u_C(R_j) + c_0\, u_0(R_j) \right],$$

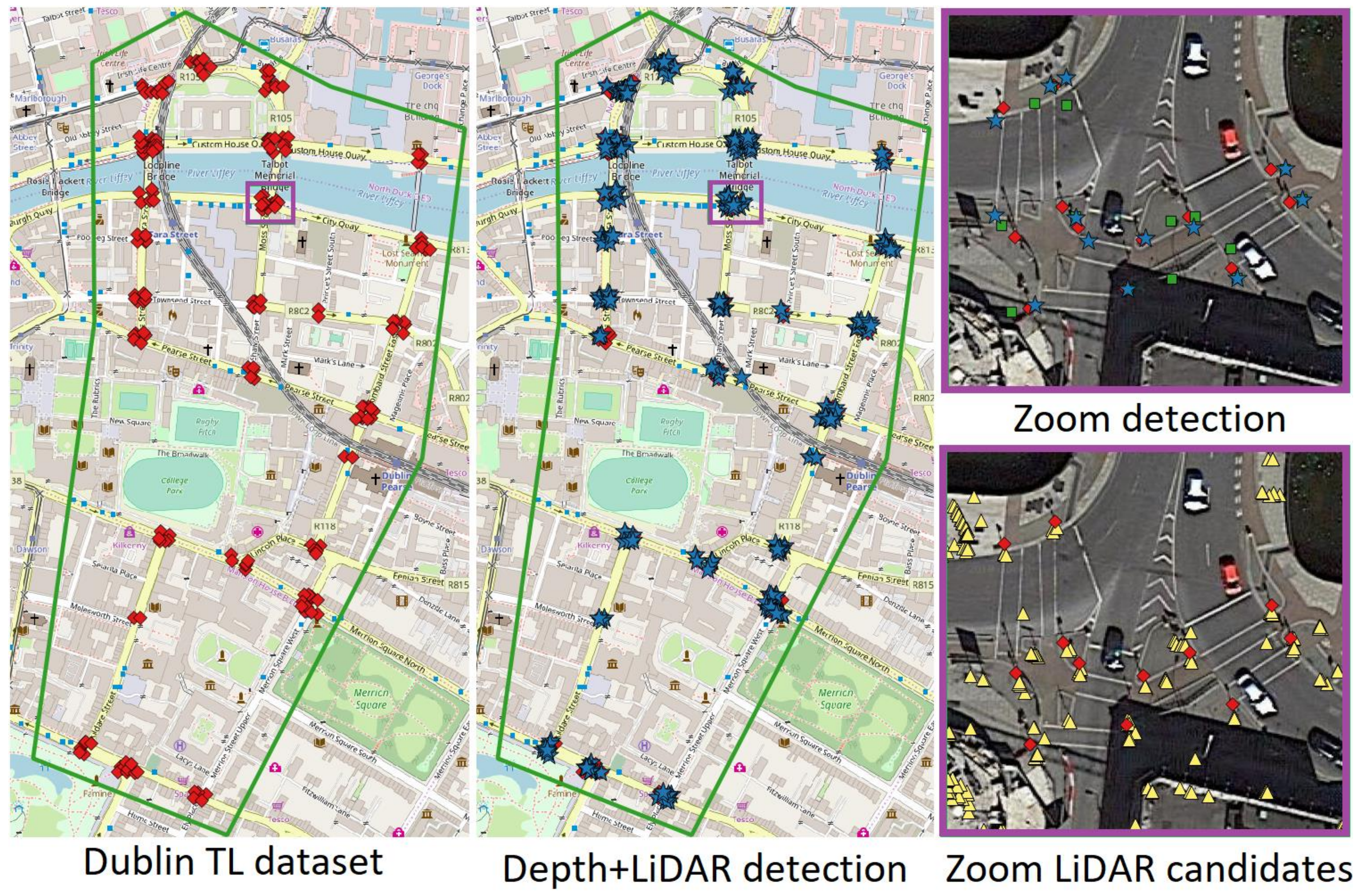
$$c_D + c_L + c_C + c_0 = 1$$

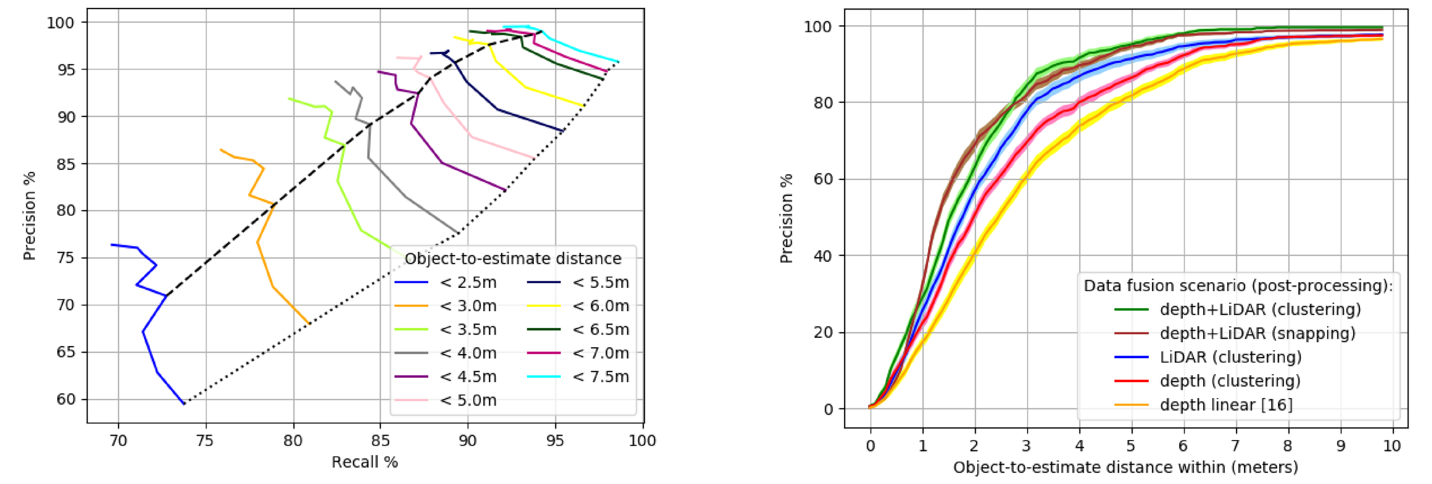
- Post-processing strategies:
  - *Clustering* via averaging (lower precision);
  - *Snapping* to LiDAR positions (lower recall).
- The same MRF-based architecture can incorporate:
  - Further image and data modalities;
  - Geometrical and position assumptions;
  - SLAM-like formulations.



## Experimental Results

- We introduce a **dataset** with 209 pole-mounted traffic lights in central Dublin.
- We employ:
  - ✓ **Google Street View** imagery: 1307 panoramas
  - ✓ **Airborne LiDAR** scan reporting 12300 pole-like matches




**an estimate is considered true positive if it is within m meters of a ground truth point.*

## Conclusion

**Fully automated** | **Customisable to various objects** | **Efficient multi-sensor fusion**

Relies on Street Level Imagery as primary detection source: performance validated on expert (*Google Street View*) and crowdsourced (*Mapillary*) imagery.

## References

[1] V. A. Krylov, E. Kenny, and R. Dahyot, "Automatic discovery and geotagging of objects from street view imagery," Remote Sens., vol. 10, no. 5, 2018.

[2] V. A. Krylov, R. Dahyot. "Object Geolocation using MRF-based Multi-sensor Fusion", Int'l Conf. Image Proc. (ICIP) 2018, Proc. ICIP 2018, pp. 2745-2749, 2018.

[3] V. A. Krylov, R. Dahyot. "Object Geolocation from Crowdsourced Street Level Imagery", European Conference on Machine Learning (ECML) Workshops, 2018.

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