A Stereo Visual Odometry Framework with Augmented Perception for Dynamic Urban Environments

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Problem statement

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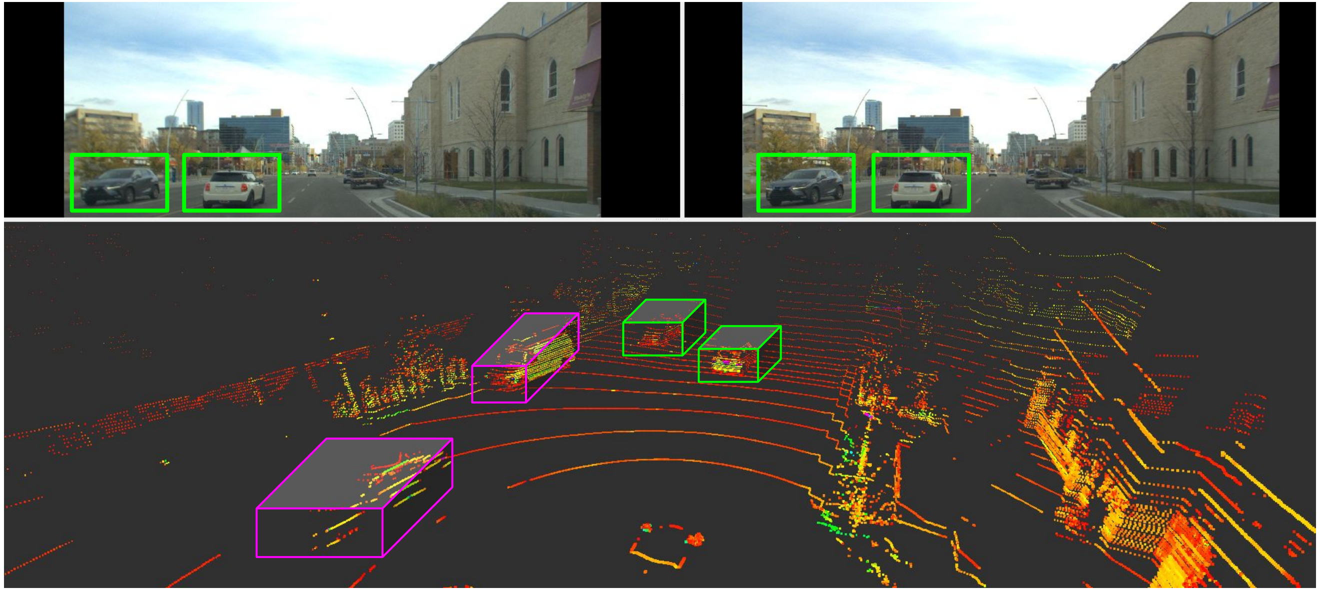
- In urban canyons, there is a significant presence of dynamic instances (vehicles and pedestrians) that generate untrackable landmarks for ego-motion estimation solutions.



Related works

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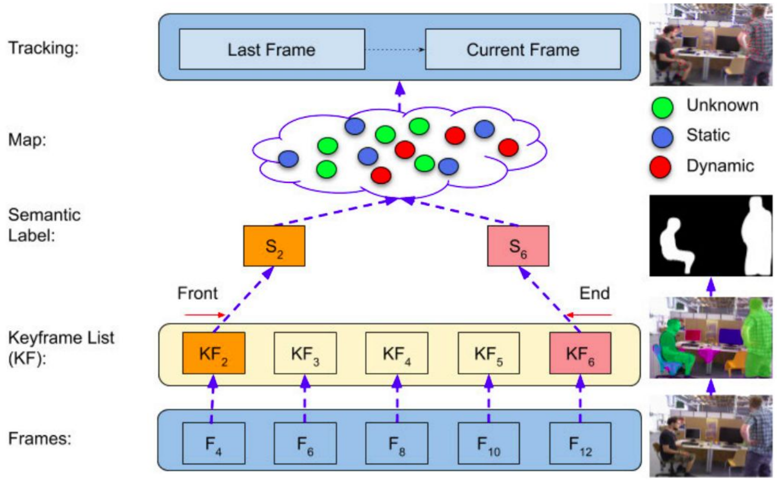
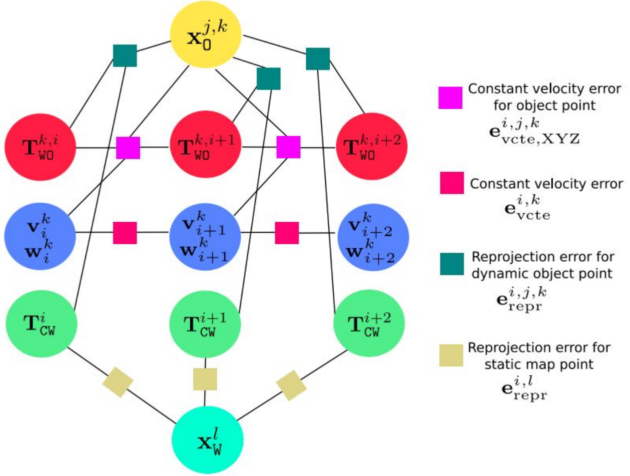
Semantic based optimization



RDS-SLAM [1]

Tightly-Coupled Multi-Object Tracking and SLAM



DynaSLAM II [2]

[1] Y. Liu and J. Miura, "Rds-slam: Real-time dynamic slam using semantic segmentation methods," IEEE Access, vol. 9, pp. 23 772– 23 785, 2021.
[2] Bescos, B., Campos, C., Tardós, J. D., & Neira, J. (2021). DynaSLAM II: Tightly-Coupled Multi-Object Tracking and SLAM. IEEE robotics and automation letters, 6(3), 5191-5198. https://doi.org/10.1109/lra.2021.3068640

Our contributions

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We propose **dynamic stereo VO** system that integrates the following characteristics:

- Compute a **union-static mask** from a **priori static street instances** by merging instance segmentation and object detection.
    - Both features and landmarks are only associated to the **static background**.

- An **efficient bundle adjustment** over **semantic-aware feature tracking** for pose refinement over a moving horizon and a sparse set of static covisible landmarks.

Dynamic SVO system overview

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We design the system that:

Dynamic SVO system overview

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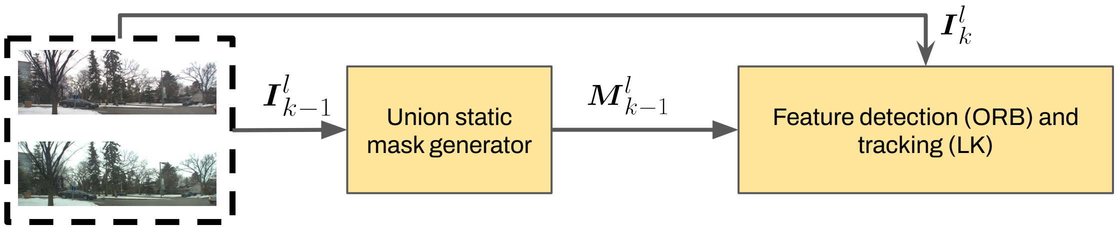
1) Computes an union static mask from merged semantics of YOLACT and YOLOv5. The feature detection filters outliers outside the static mask, and inliers are tracked to current frame.



Stereo frame [k]
and Left image[k-1]

SVO algorithm overview

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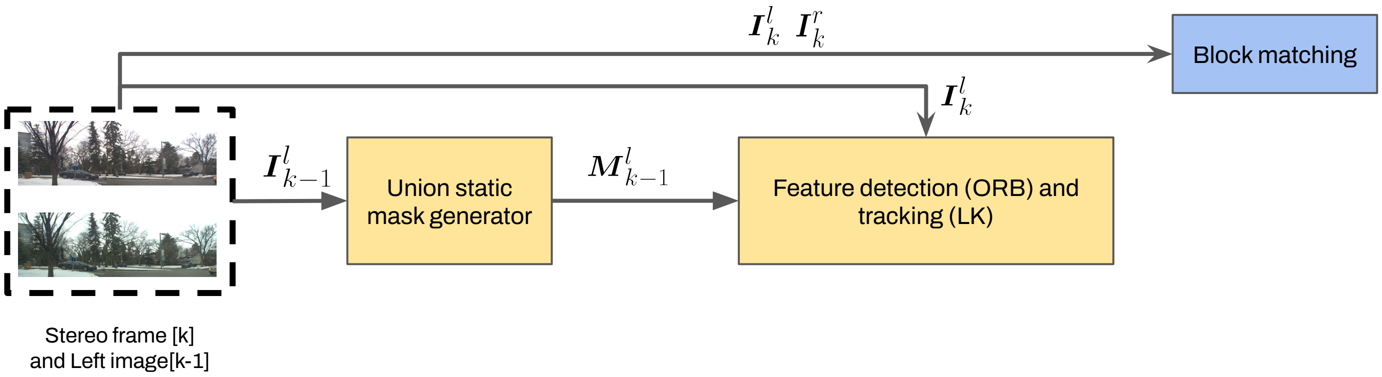
2) Block matches left and right frame to get disparity map and compute right features.



SVO algorithm overview

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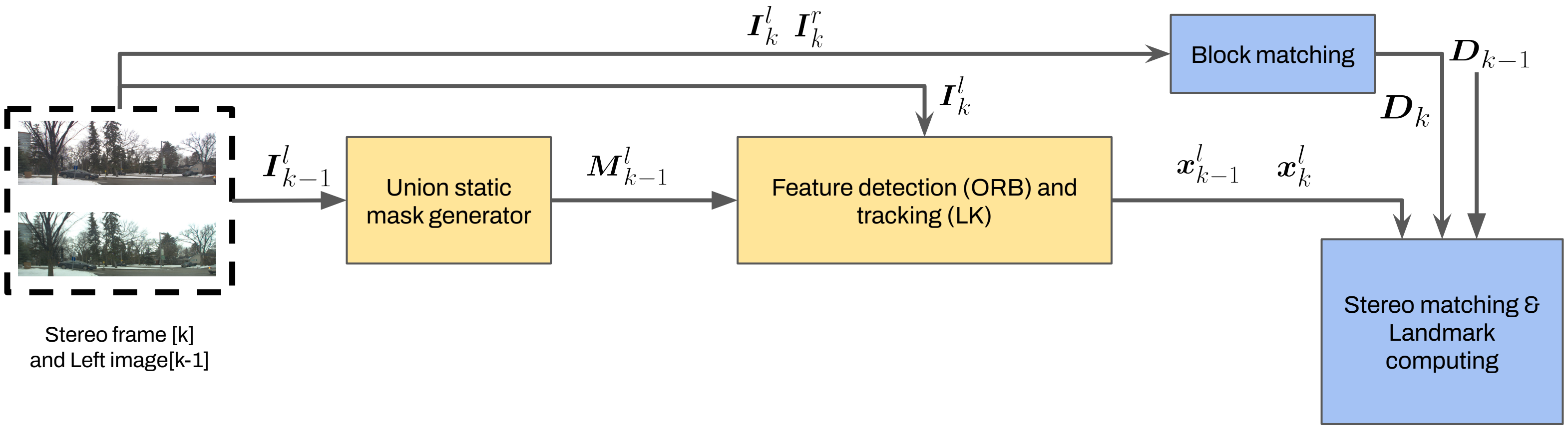
2) Block matches left and right frame to get disparity map and right features without detection. Then, landmarks are triangulated to form a local point cloud.



SVO algorithm overview

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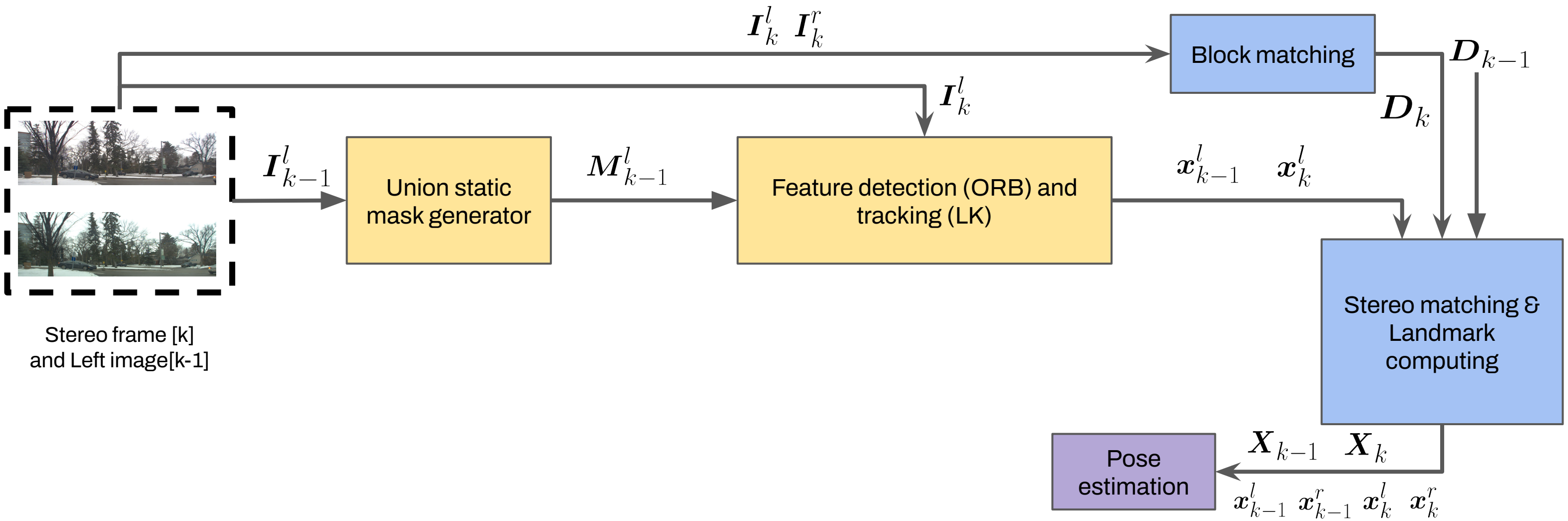
2) Relative pose T (from k-1 to k) is estimated from optimization problem:

Eq(1)
$$\underset{{}^{k}\boldsymbol{T}_{k-1}}{\operatorname{argmin}} \left\| \boldsymbol{x}_k^l - \pi(\boldsymbol{X}_{k-1}, \boldsymbol{P}^l, {}^{k}\boldsymbol{T}_{k-1}) \right\|^2 + \left\| \boldsymbol{x}_{k-1}^l - \pi\left(\boldsymbol{X}_k, \boldsymbol{P}^l, {}^{k-1}\boldsymbol{T}_k\right) \right\|^2$$



SVO algorithm overview

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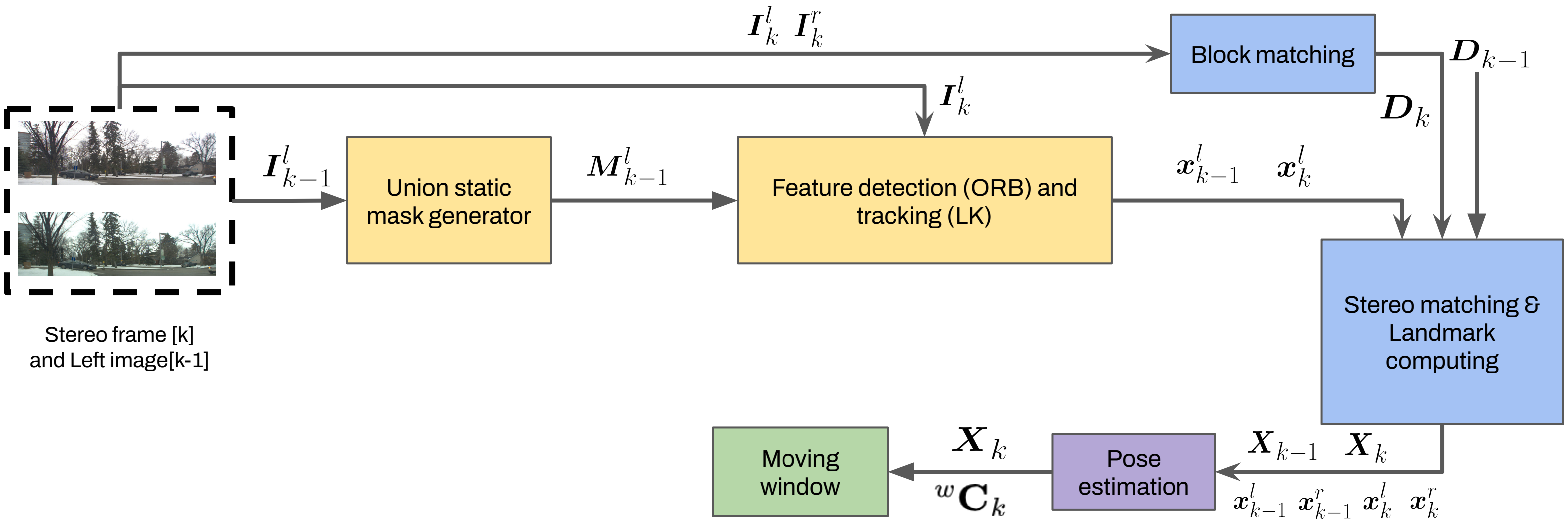
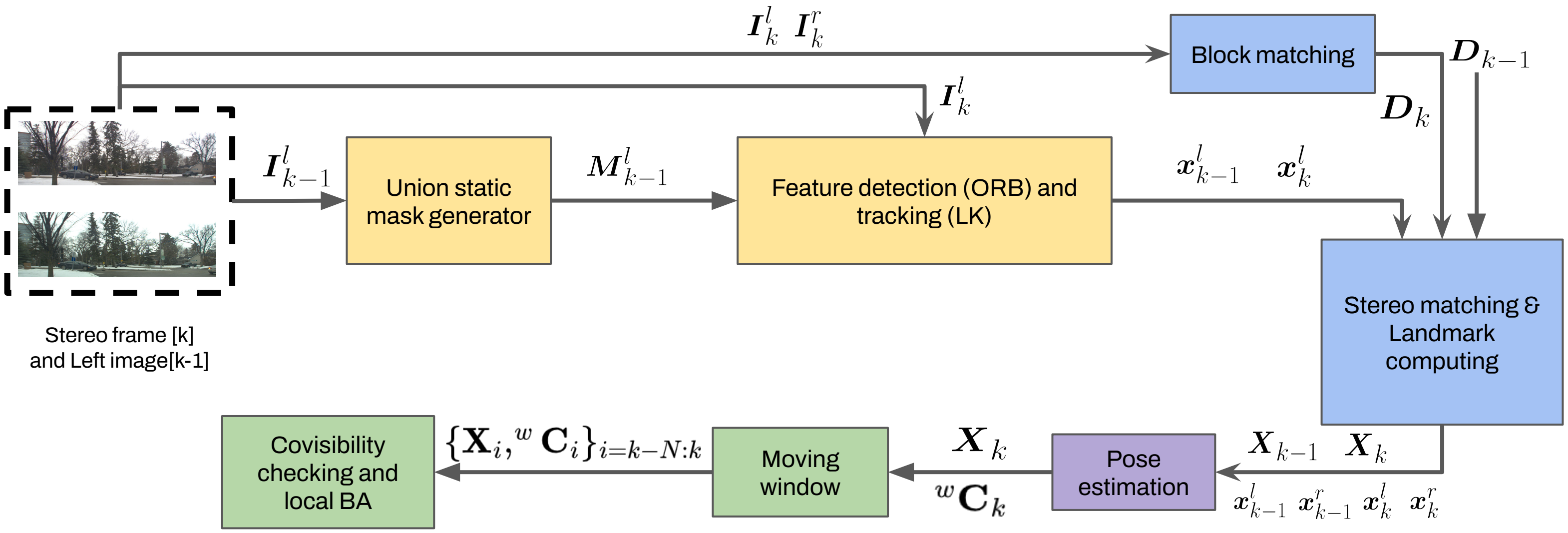
4) Current pose C and landmarks in global frame are append to a moving window that consider N last frames.



SVO algorithm overview

4) Current pose C and landmarks in global frame are append to a moving window that consider N last frames. Covisibility checking ensures node connections.



Urban union static mask

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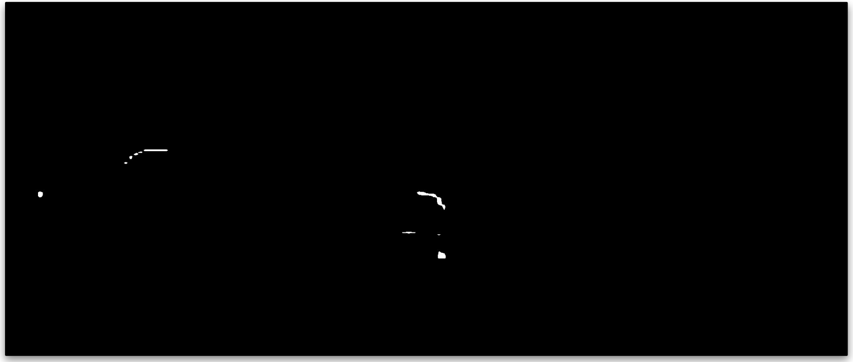
- In urban canyons, we have certainty that there are static objects which cannot be moveable, thus avoiding movement discrimination in dynamic instance filtering.

RGB-D image



Light poles **U** *traffic lights* **U** *traffic signs* (from YOLACT[3])

[3] D. Bolya, C. Zhou, F. Xiao, and Y. J. Lee, “YOLACT: real-time instance segmentation,” CoRR, vol. abs/1904.02689, 2019.

Urban union static mask

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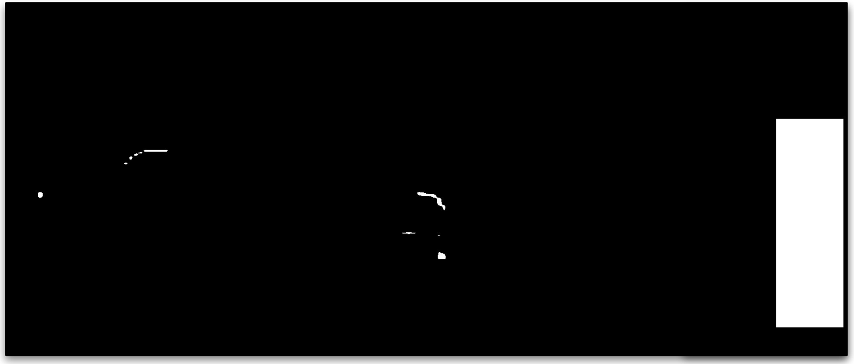
RGB-D image



Light poles **U** *traffic lights* **U** *traffic signs*
U *tree trunk* (from YOLOv5[4])

[4] J. Solawetz, “What is YOLOv5? A Guide for Beginners.” 1 2023.

Urban union static mask

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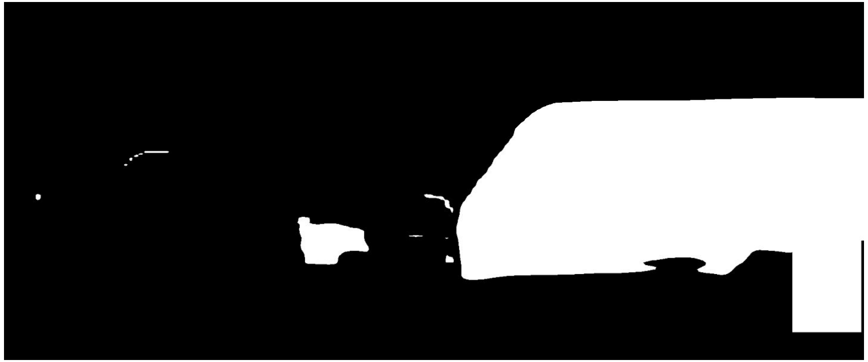
RGB-D image



Light poles **U** *traffic lights* **U** *traffic signs* **U** *tree trunk* **U** *buildings* (from YOLACT[3])

Urban union static mask

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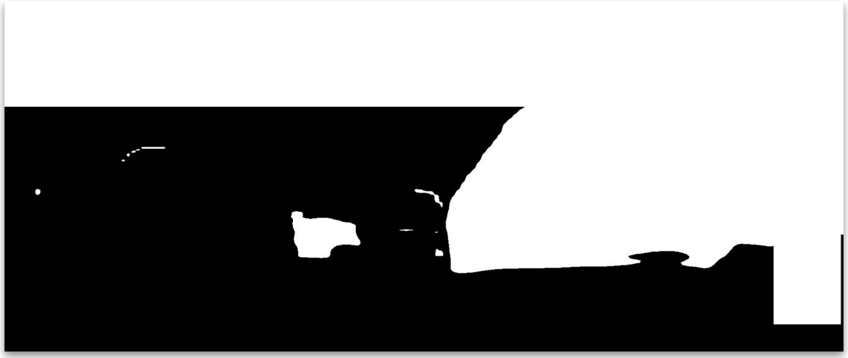
- A 30% upper image (tunnable depending on scene content) has been added to the mask to increase robustness against false positives in segmentation and detection.

RGB-D image



Light poles **U** *traffic lights* **U** *traffic signs* **U** *tree trunk* **U** *buildings* **U** *30%upper image*

Covisibility graph with static landmarks

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- Took inspiration of ORB-SLAM [5] and Strasdat.et al [6] to adapt a covisibility graph to connect consecutive frames, map points and feature measurements.

Covisibility graph with static landmarks

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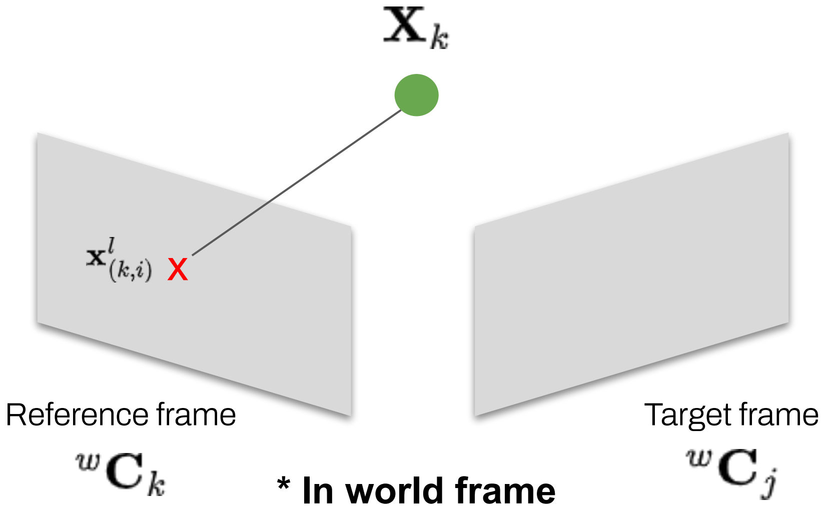
- Took inspiration of ORB-SLAM [5] and Strasdat.et al [6] to adapt a covisibility graph to connect consecutive frames, map points and feature measurements.



Algorithm 2: Covisibility check for one frame

Initial : reference frame ${}^wC_k$, graph $\mathcal{C}$
Parameters: image dimensions (h, w)
$X_k = {}^w C_k X_k$;

[5] R. Mur-Artal, J. M. M. Montiel, and J. D. Tard ́os, “ORB-SLAM: a versatile and accurate monocular SLAM system,” CoRR, vol. abs/1502.00956, 2015.
[6] H. Strasdat, A. J. Davison, J. Montiel, and K. Konolige, “Double window optimisation for constant time visual slam,” in 2011 IEEE ICCV, 2011, pp. 2352–2359.

Covisibility graph with static landmarks

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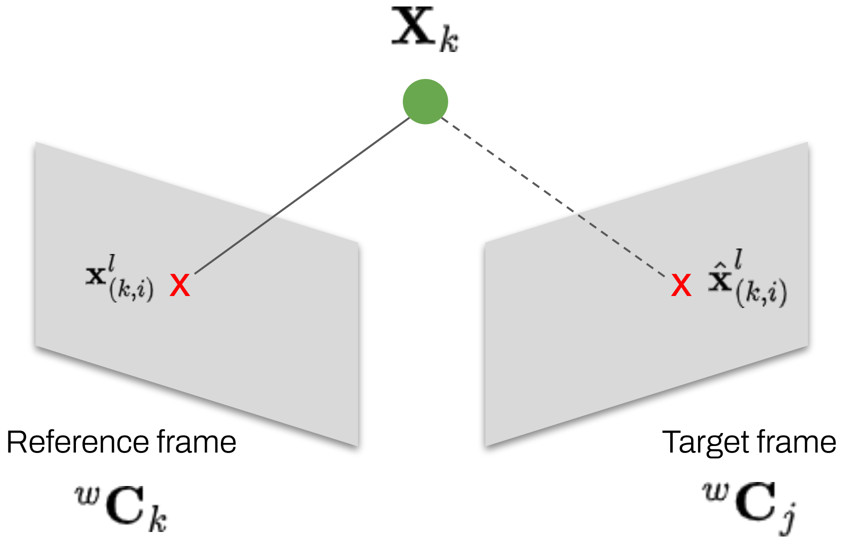
- The static information is embedded in the graph



Algorithm 2: Covisibility check for one frame

Initial : reference frame ${}^wC_k$, graph $\mathcal{C}$
Parameters: image dimensions (h, w)
$X_k = {}^wC_k X_k$;
for *frame j in* $\mathcal{F} \leftarrow \mathcal{C}$ **do**
  if ${}^wC_j == {}^wC_k$ **then**
    pass;
  $\hat{x}^l_j = \pi(X_k, P^l, ({}^wC_j)^{-1})$;

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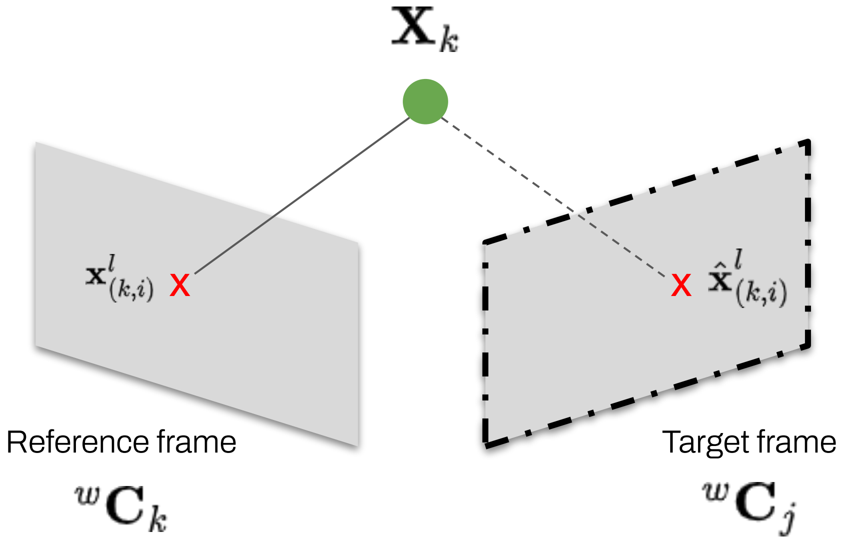
Covisibility graph with static landmarks



Algorithm 2: Covisibility check for one frame

Initial : reference frame ${}^wC_k$, graph $\mathcal{C}$
Parameters: image dimensions (h, w)
$X_k =^w C_k X_k$;
for *frame* j *in* $\mathcal{F} \leftarrow \mathcal{C}$ **do**
  if ${}^wC_j ==^w C_k$ **then**
    pass;
  $\hat{x}^l_j = \pi(X_k, P^l, ({}^wC_j)^{-1})$;
  for *point* i *in* $\hat{x}^l_j$ **do**
    if $\hat{x}^l_{(j,i)} \notin [h, w]$ **then**
      Reject $x^l_{k,i}, X_{k,i}$ in next steps;
  end

Covisibility graph with static landmarks

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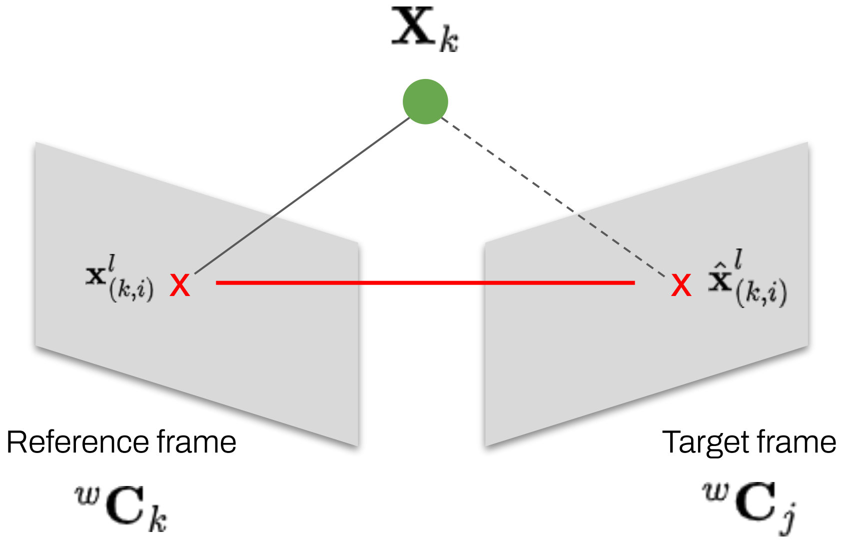

Algorithm 2: Covisibility check for one frame

Initial : reference frame ^wC_k, graph $\mathcal{C}$
Parameters: image dimensions (h, w)
$\boldsymbol{X}_k =^w C_k \boldsymbol{X}_k$;
for *frame* j *in* $\mathcal{F} \leftarrow \mathcal{C}$ **do**
  if $^wC_j ==^w C_k$ **then**
    pass;
  $\hat{x}^l_j = \pi(\boldsymbol{X}_k, \boldsymbol{P}^l, (^w\boldsymbol{C}_j)^{-1})$;
  for *point* i *in* $\hat{x}^l_j$ **do**
    if $\hat{x}^l_{(j,i)} \notin [h, w]$ **then**
      Reject $\boldsymbol{x}^l_{k,i}, \boldsymbol{X}_{k,i}$ in next steps;
  end
  $\mathcal{M} \leftarrow \mathcal{FM}(\boldsymbol{d}^l_k \leftarrow \boldsymbol{x}^l_k, \boldsymbol{d}^l_j \leftarrow \boldsymbol{x}^l_j)$;
  for (m', m) *in matches* $\mathcal{M}$ **do**
    Add observation $(^w\boldsymbol{C}_j, \boldsymbol{x}^l_{(j,m)})$ in $\boldsymbol{X}_{(k,m')}$;
  end
end

Covisibility graph with static landmarks

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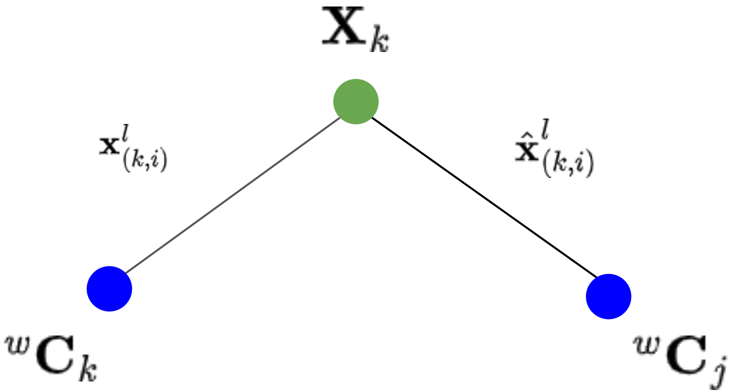
Local bundle adjustment graph



extended to cover all the window poses and associated landmarks ...

The graphs contains only static information.

Evaluation platform

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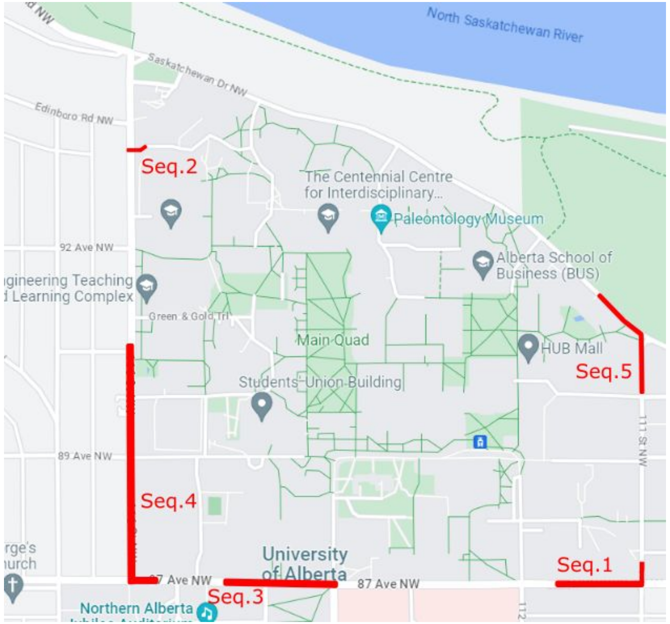
NODE Lab test car

Map view of test sequences



Trajectory results & comparison with SOTA

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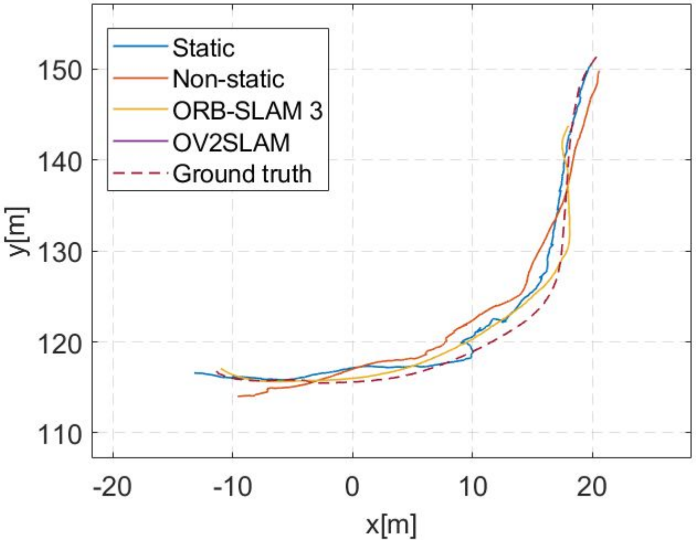
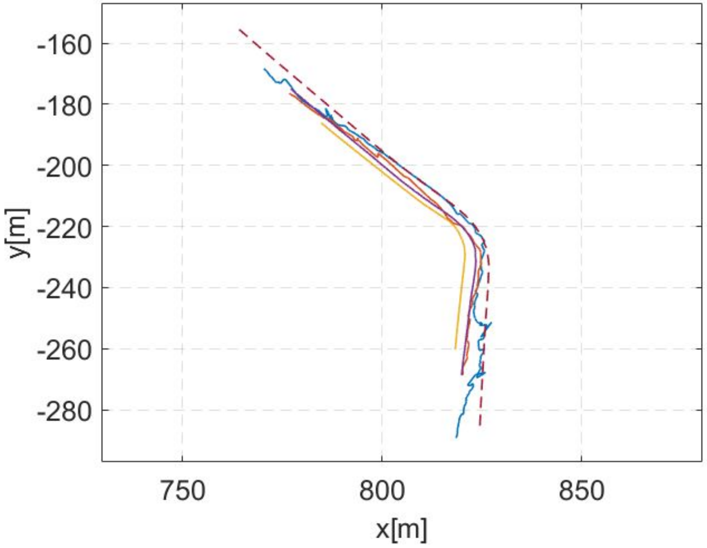
The method handles scenarios under presence of dynamic objects (pedestrians and moving cars).

Sequence 2



Sequence 5



Quantitative results

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Seq.	Evaluation metric: ATE_T[m], ATE_R[rad]			
	Ours(static)	Ours(non-static)	ORB-SLAM 3	OV2SLAM
1	**5.165** / **0.455**	7.591 / 0.457	36.984 / 0.964	22.113 / 0.829
2	**1.975** / 0.356	2.544 / 0.288	2.822 / **0.090**	3.992 / 0.653
3	**6.577** / 0.517	8.377 / 0.562	24.867 / **0.106**	36.653 / 0.588
4	**10.349** / 0.506	12.402 / 0.336	25.052 / 0.143	16.579 / **0.140**
5	**6.959** / 0.357	10.863 / 0.474	17.72 / **0.123**	11.391 / 0.136

TABLE I: Comparison of different algorithms in dynamic sequences from NODE Lab dataset

*Best results are shown in **bold**

Processing time comparison

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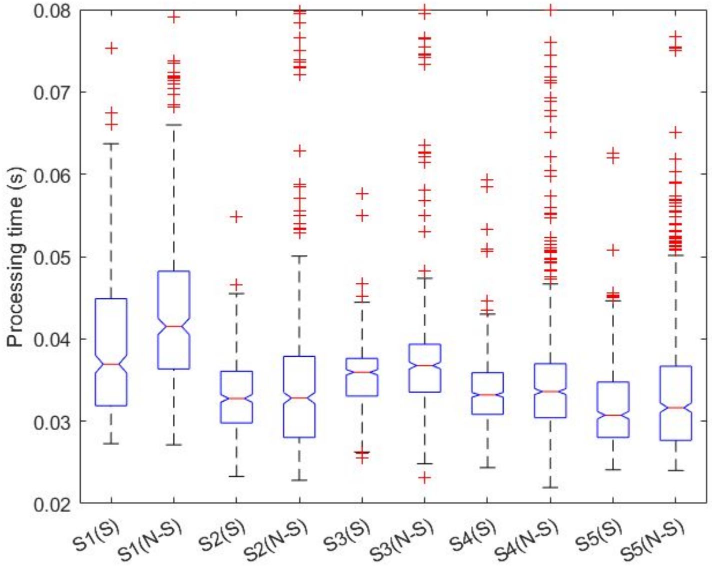
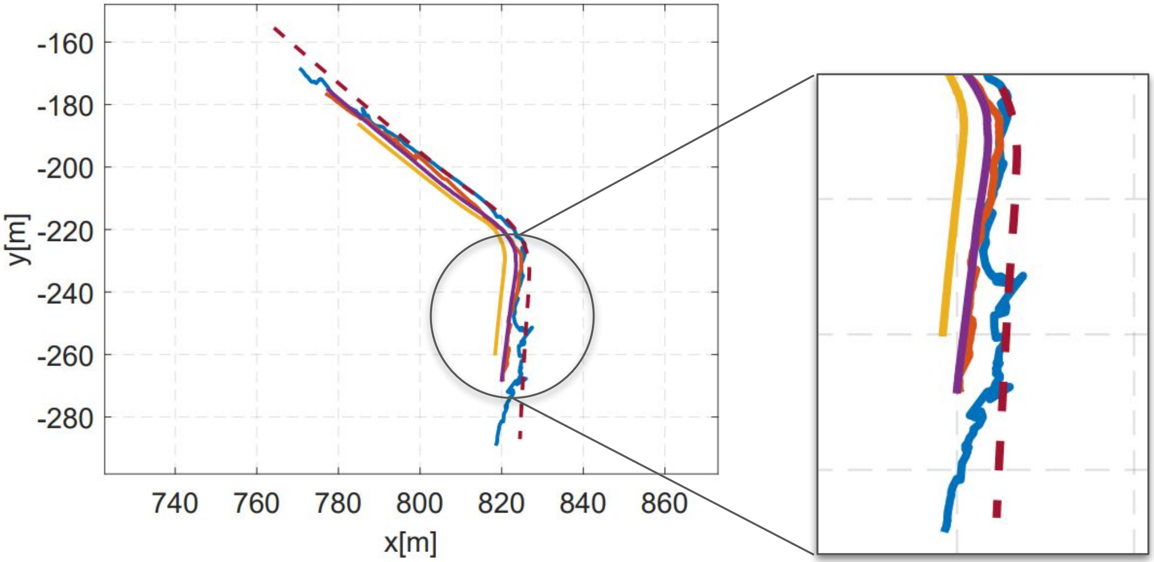
The sparse set of static features reduces computational load in stages of stereo matching, triangulation and pose estimation in comparison to use the non-static set.



Issues and future works



Temporal instability on instance segmentation or object detection due to **occlusion**, **fast movement** or **incapability to process far objects** injects noise in estimation.

Conclusions

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- A semantic-aware stereo visual odometry has been presented which identifies street objects to include them in static ROI for reliable feature extraction.

- Static features, landmarks and poses were wrapped inside a local bundle adjustment optimization. The refinement BA is benefited by using a reduced set of keypoints for faster and more accurate results.

- The effectiveness of the method has been demonstrated through extended evaluation on urban canyons (University of Alberta) against other methods.

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Thank You!

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