Matched-Filter based LiDAR Place Recognition for Urban and Natural Environments

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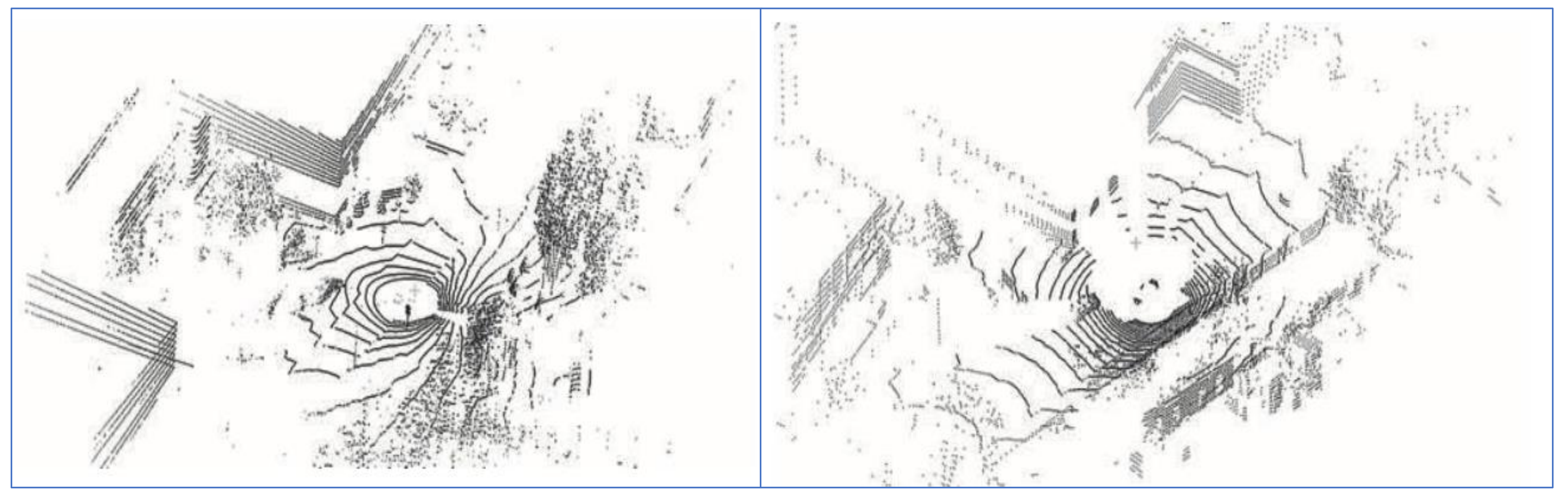
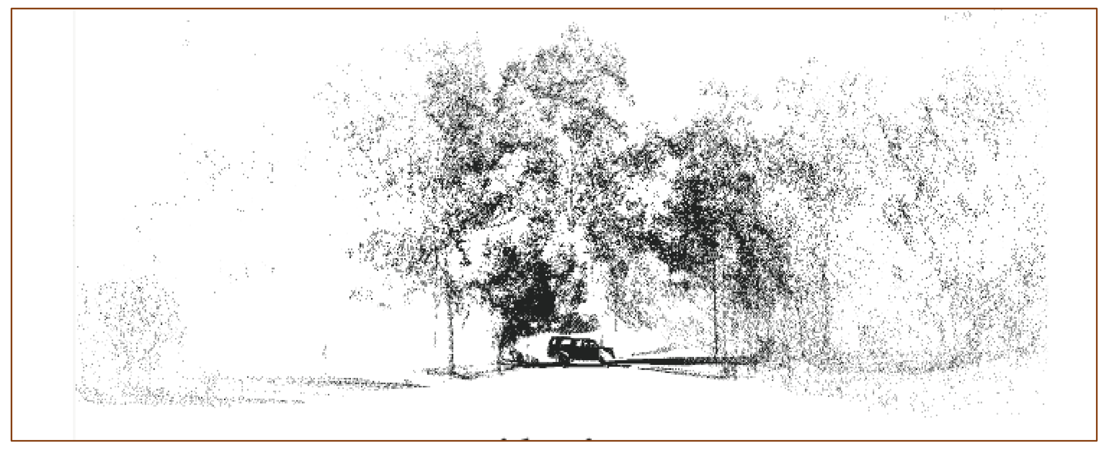
Motivation

Place recognition enables robots to determine their location, and LiDAR sensors are more robust to lighting changes and certain weather conditions than cameras. We therefore propose a method that performs matched filtering on bird's eye view (BEV) descriptors with a global-to-local search, requiring minimal hyperparameter tuning and achieving up to 15% improvement across LPR benchmarks in urban and natural environments.



LiDAR scans from two popular LPR datasets (NCLT and Oxford Radar)



LiDAR scan from an unstructured environment dataset (WildPlaces)

Existing Methods for LiDAR place recognition

- Handcrafted descriptors [1,2,3,4] compress 3D scans into compact, rotation-tolerant representations.
- Learned descriptors [5,6,7,8] achieves higher recall and robustness by training on large-scale LiDAR datasets from structured urban settings with stable features like buildings, poles, and road edges. However, their performance drops in unstructured or natural environments (forests, trails, foliage) where geometry is irregular and changes over time [9].

Acknowledgements

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References

[1,2,3] He et al., IROS 2016 (M2DP); Kim & Kim, IROS 2018 (Scan Context); Xu et al., TRO 2022 (RING++); Wang et al., [4, 5,6,7,8, 9] IROS-2020 (LiDAR-Iris), Uy et al., CVPR 2018 (PointNetVLAD), Zhang et al., CVPR 2019 (PCAN), Liu et al., ICCV 2019 (LPD-Net), Du et al., CVPR 2020 (DH3D), Knights et al., RA-L 2024 (GeoAdapt)

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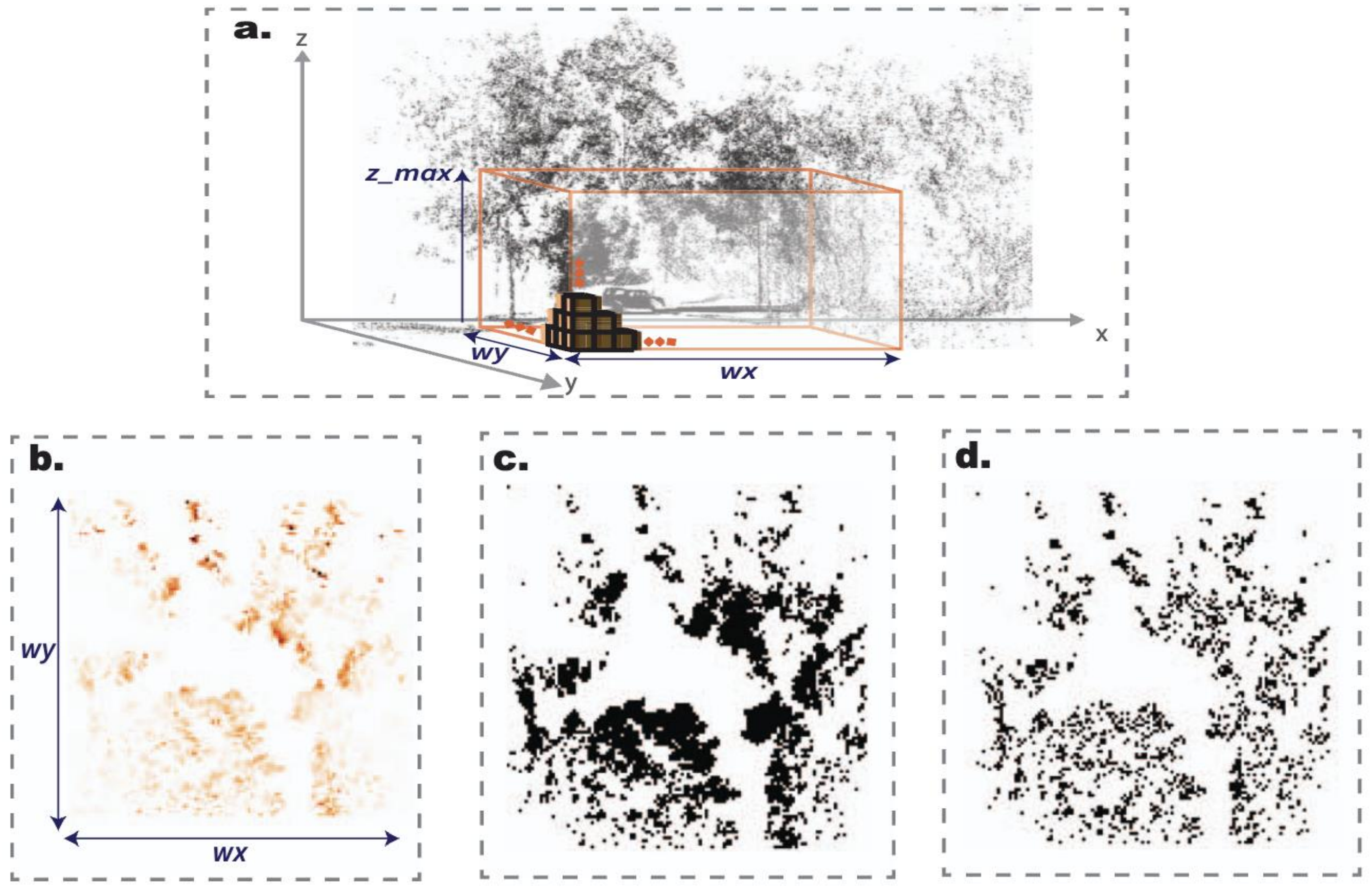
https://github.com/theresejoseph/Matched_Filter_based_LPR

Methodology

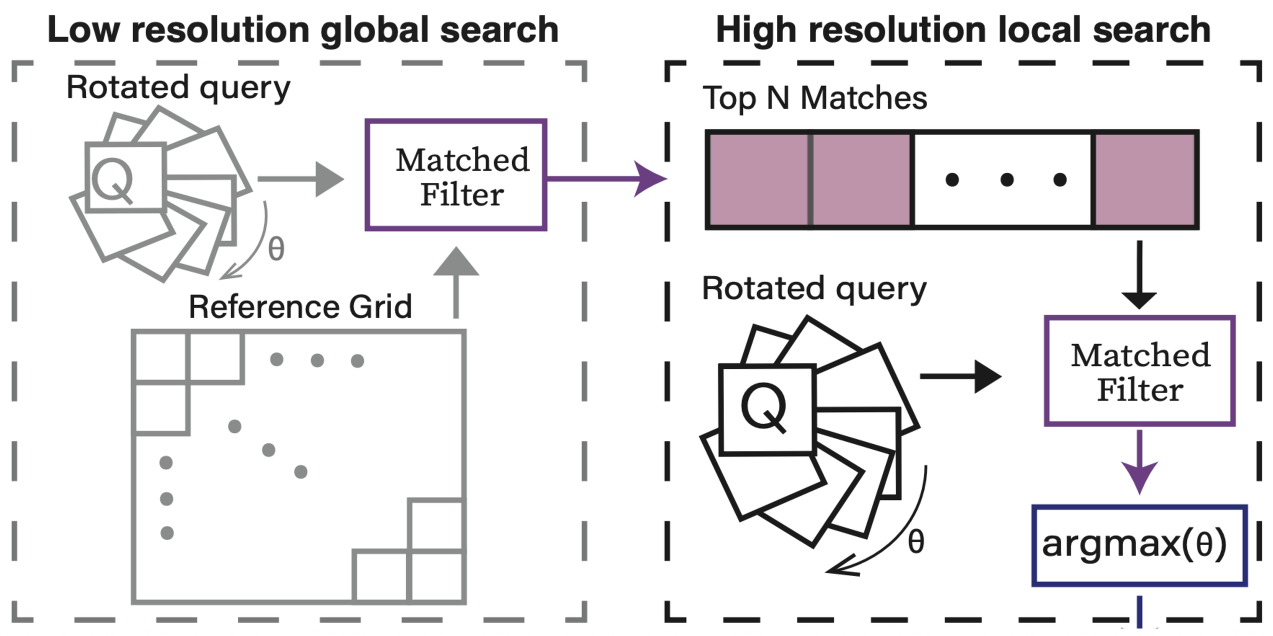
Generating 2D Descriptors

- The 3D LiDAR scan is transformed into a 2D birds eye view descriptor with voxelisation, height density-based occupancy and patch down-sampling.



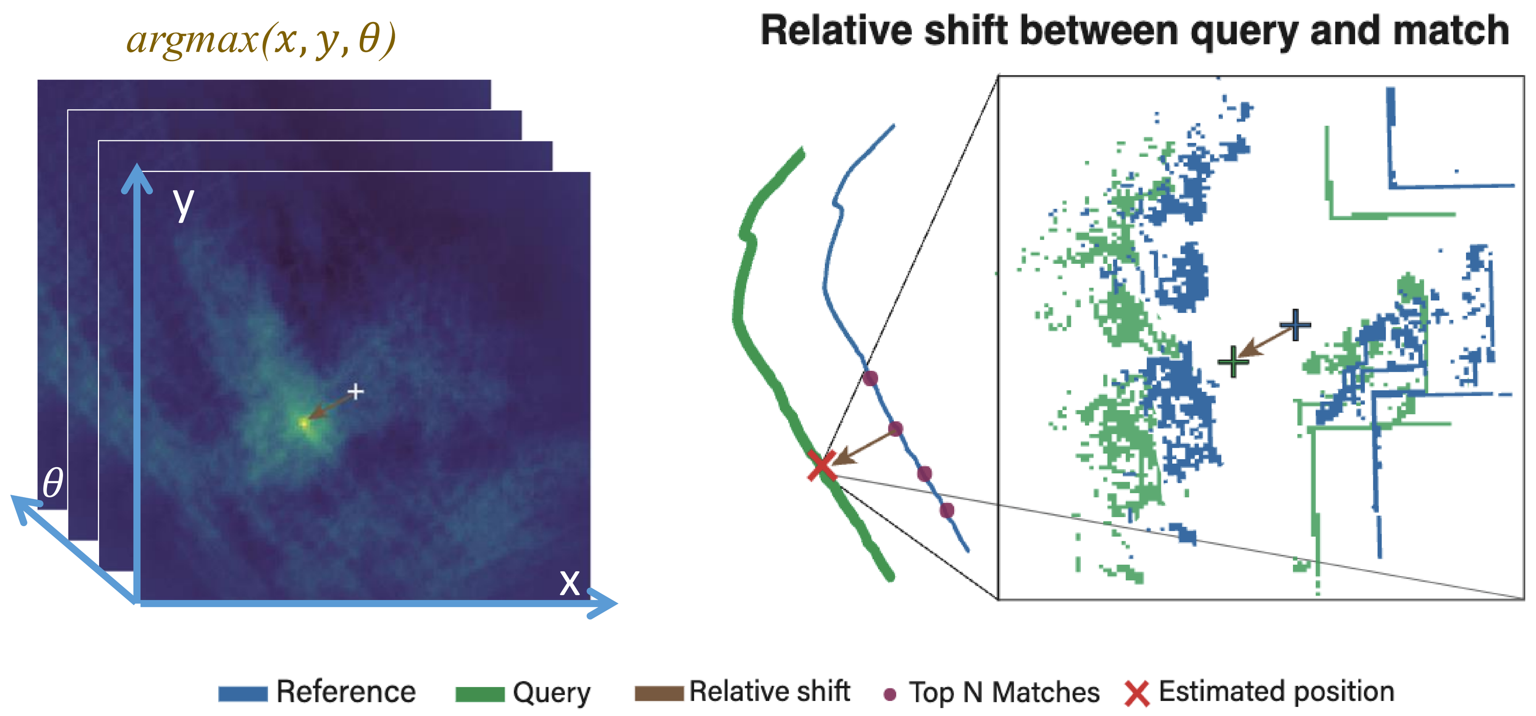
Matched Filtering with LiDAR BEV Descriptors

- The query LiDAR descriptors are rotated and convolved against the reference database with a two-stage search.



$$(\mathbf{Q} * \mathbf{R})(i_r, j_r, \theta) = \sum_{i_q} \sum_{j_q} \mathbf{Q}(i_q, j_q, \theta) \cdot \mathbf{R}(i_q + i_r, j_q + j_r, 0).$$

Direct Relative Pose Estimation from Matched Filter Output



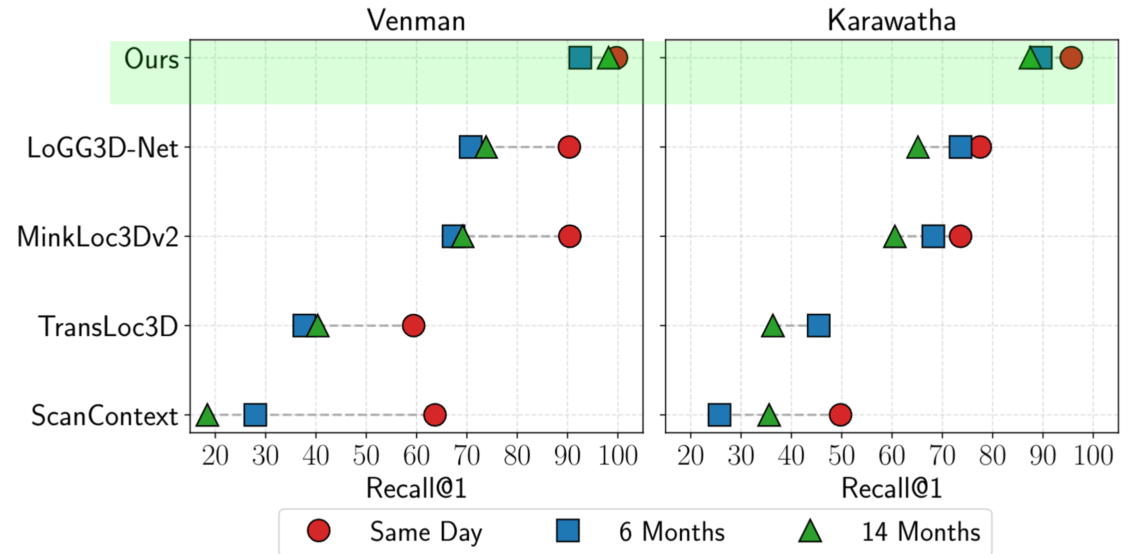
Results

Average Recall@1 across urban and natural environments

Structured Environments		
Method	Oxford Radar	NCLT
M2DP	50.9	36.2
PN-VLAD	86.6	62.8
PCAN	80.3	59.0
LPD-Net	90.0	72.5
DH3D	78.2	59.4
BVMatch	93.9	83.6
Ours	**94.6**	**92.9**

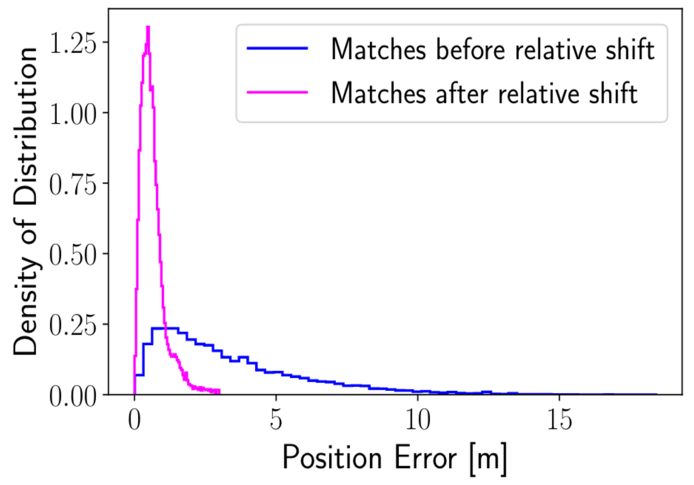
Natural Environments (WildPlaces)			
Method	Venman	Karawatha	Average
Scan Context	33.98	38.44	36.21
TransLoc3D	50.24	46.08	48.16
MinkLoc3Dv2	75.77	67.82	71.80
LoGG3D-Net	79.84	74.67	77.26
Ours	**94.46**	**90.50**	**92.48**

- Our method maintains **high recall over time**, even with 6- and 14-month environmental changes in WildPlaces .



- **Direct pose estimation** has lowest translation error and competitive rotational error without ICP or RANSAC
- Correcting relative shift for the matched scan **reduced the variance in position error**, improving overall localisation

	RTE (m)		RRE (deg)		SR (%)
Method	Mean	Std.	Mean	Std.	
SIFT	0.69	0.46	1.49	1.23	53.3
DH3D	1.16	0.54	3.43	1.06	14.8
OverlapNet	–	–	2.43	1.42	15.4
BVMatch	0.57	0.38	**1.08**	**1.00**	94.5
Ours	**0.48**	**0.29**	1.43	1.07	**97.7**



- Limitations include scalability with very large reference maps and hyperparameter tuning requirements for novel environments.