Differentiable SLAM Helps Deep Learning-based LiDAR Perception Tasks

Prashant Kumar[1], Dheeraj Vattikonda[2], Vedang Bhupesh Shenvi Nadkarni[3] , Erqun Dong[2], Sabyasachi Sahoo[4]
[1]Indian Institute of Technology, Delhi, India [2]McGill University, MILA [3]BITS Pilani, India [4]Université Laval, MILA

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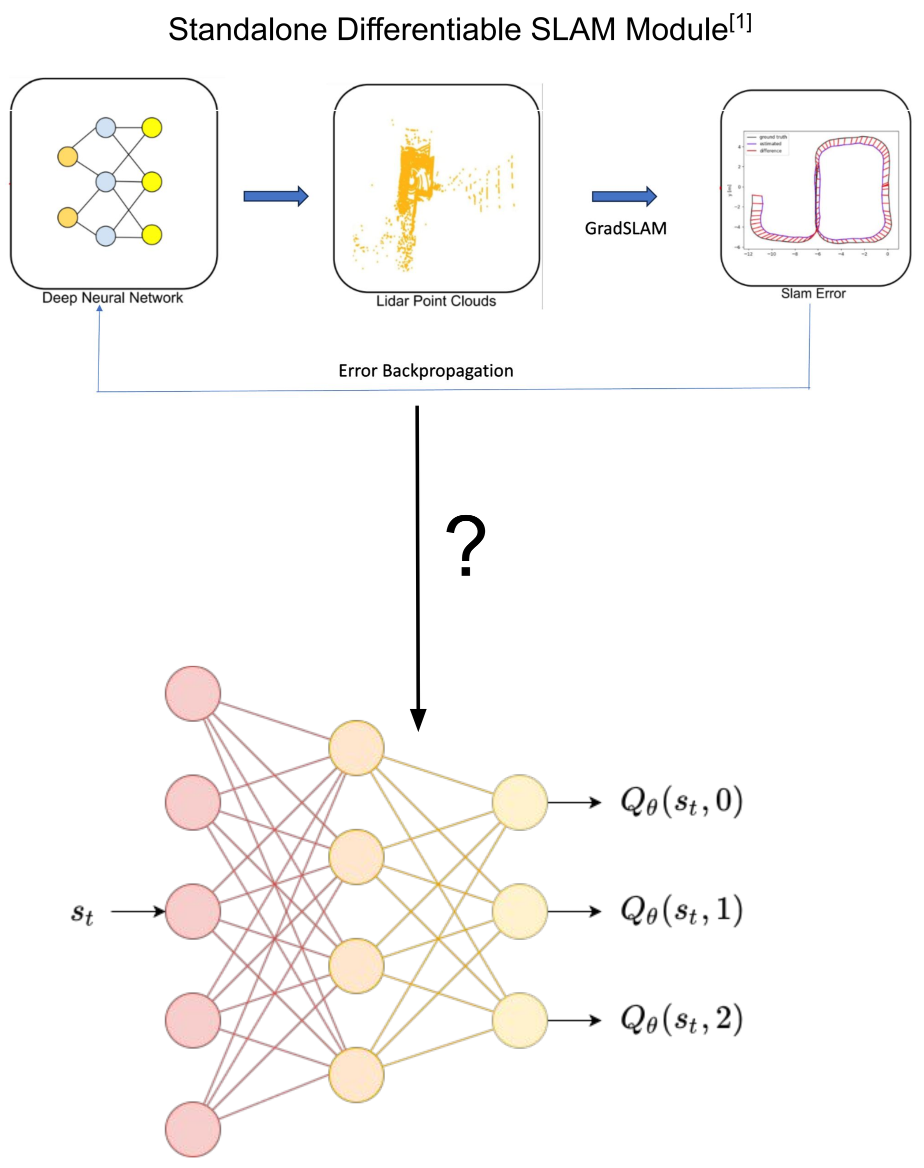
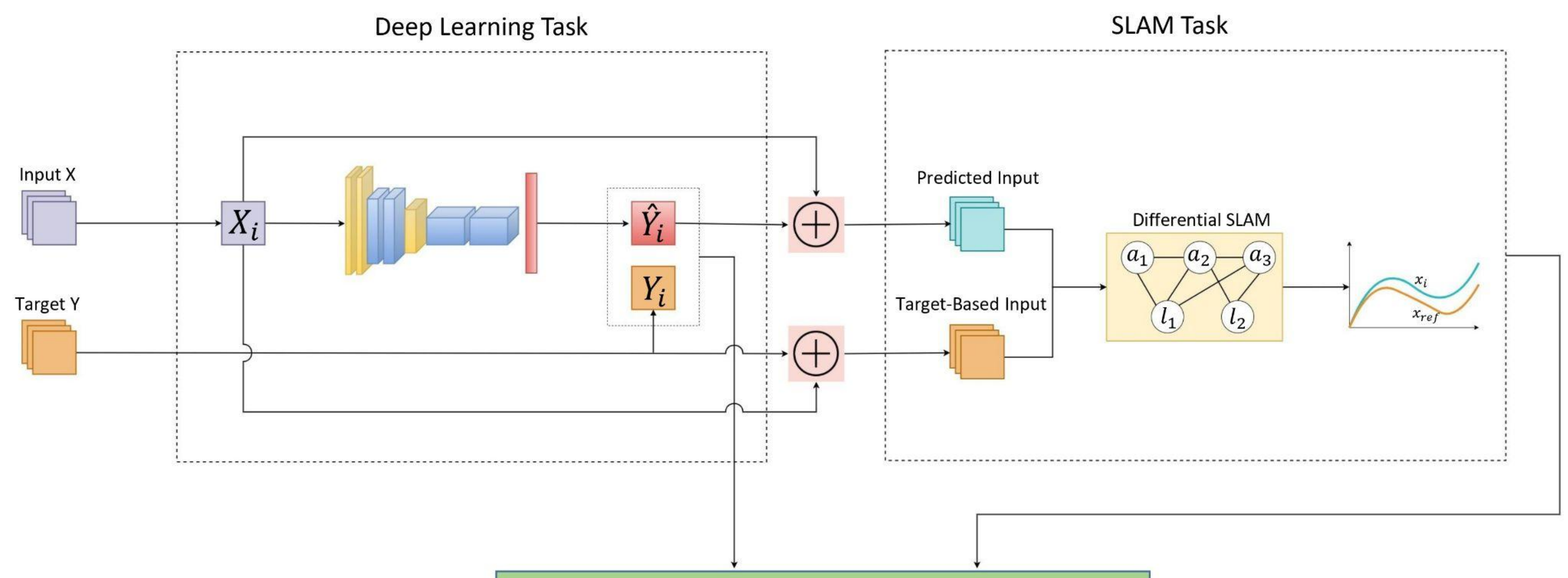
Differentiable SLAM Integration in DL Application is still unsolved



Integration of LiDAR SLAM to DL pipelines as a trainable Loss is an open problem.

Our proposal - Self Supervised Differentiable SLAM for DL applications



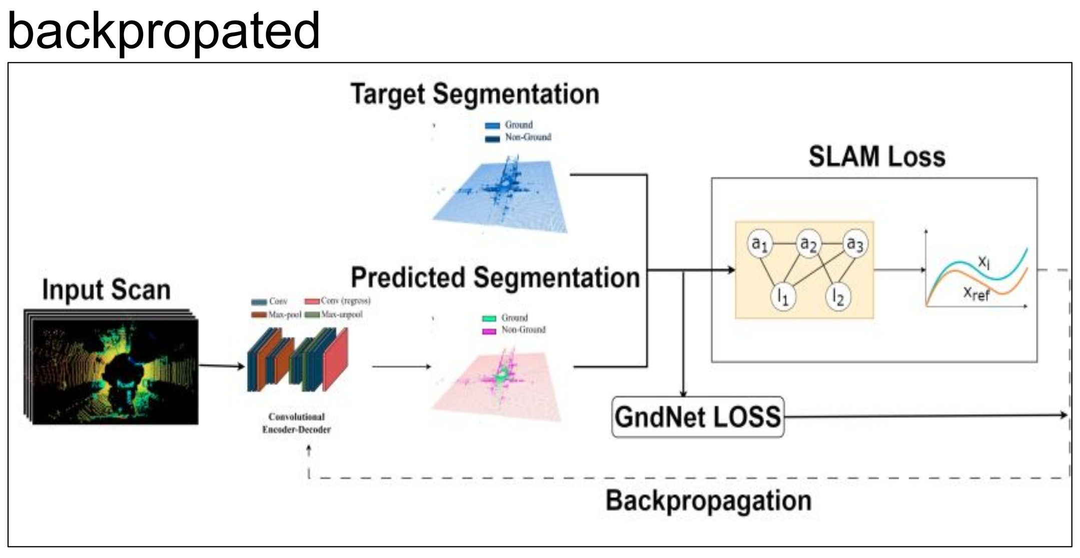
$$L = \left\{ \frac{1}{n} \sum_{i=1}^{n} l(f(X_i;\theta), Y_i) + \beta R(\theta) \right\} + \left\{ \frac{1}{n} \sum_{i=1}^{n} ||x_i - x_{ref}||^2 \right\}$$

- A deep learning task - takes the input scans (X_i) and outputs a per LiDAR point prediction (classification or regression).
- A task specific selection criteria selects points from the input and corresponding points based on the output prediction (e.g an elevation estimation DL task selects points only above a threshold).
- SLAM using (Translation and Rotational Error) contiguous input and predicted scans generates trajectory estimates for both. Deviation of the predicted scans' trajectory from the input estimated trajectory contributes to SLAM error that is back- propagated.

Applications to test Differentiable SLAM

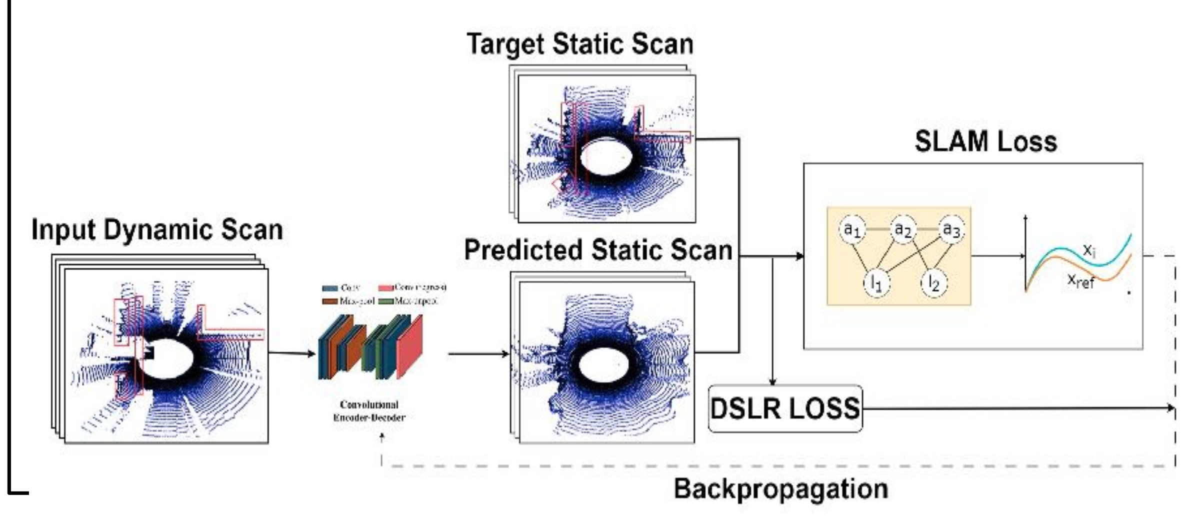
GnDNet - Ground Elevation Estimation

- Point elevation prediction using differentiable SLAM Loss - calculated between predicted non-ground points (target) for ground-truth non-ground points (source).
- Points corresponding to predicted elevations beyond a certain threshold (selection criteria) form the target.
- SLAM loss between the source and target is backpropated



DSLR - Dynamic to Static Image Translation

- Accurate static translation with diff. SLAM loss between predicted static structures (target) and ground truth static structures.
- All predicted points form the target LiDAR scan. No explicit selection criteria.
- SLAM Loss between the G.T. static and target static scans is backpropagated.



Generative Model - LiDAR Reconstruction

- Help in Precise LiDAR Reconstruction using differentiable SLAM error between reconstructed and groundtruth LiDAR.
- Pipeline same as for DSLR. No explicit selection criteria.

Semantic Segmentation

- Per point multi-class classification problem
- Selection criteria requires selecting selecting predicted non-moving classes (e.g. walls, parking) for SLAM.
- Selection criteria requires non - differentiable operations- torch.isin(), torch.argmax()
- Backpropagation computation graph gets disconnected. SLAM Loss cannot be backpropagated.
- Our module does not work in these settings.

Experiments and Results

GndNet Comparsion Results

Method	Frames	MSE	mIOU	Prec	Recall
GndNet	6554	0.76	**0.81**	**0.85**	0.94
GndNet+Diff SLAM	6554	**0.72**	**0.81**	0.83	**0.97**

Comparison of Ground Elevation Estimation and Segmentation of ground and non-ground points with and without differentiable SLAM module.

Run	With Diff SLAM			Without Diff SLAM		
	ATE	RPE		ATE	RPE	
		Trans	Rot		Trans	Rot
CARLA-64 Dataset						
0	**2.37**	**0.440**	**0.09**	4.73	**0.440**	0.11
1	**1.3**	**0.400**	**0.070**	2.9	**0.400**	**0.070**
2	**0.76**	**0.567**	**0.07**	1.36	0.571	0.15
3	**4.09**	0.399	**0.081**	4.4	**0.395**	0.104
ARD-16 Dataset						
3	**1.94**	**4.81**	**0.186**	2.05	**4.81**	0.188

Comparison of SLAM Results for DSLR with and without Diff. SLAM on CARLA-64 and ARD-16

DSLR Comparison Results

Dataset	Run	DSLR with Diff. SLAM	DSLR without Diff. SLAM
CARLA-64	9	**4.15**	4.24
	10	**14.55**	16.24
	11	**6.22**	7.63
	12	4.63	**4.45**
	13	**6.62**	8.20
	14	**5.59**	6.31
ARD-16	3	**0.31**	0.34
KITTI	8	**5.00**	5.23

Comparison of Static Reconstruction results of DSLR using Chamfer's Distance metric on 3 datasets with and without differentiable SLAM module.

Generative Model Comparsion

CARLA-64	Chamfer's Distance with SLAM	Chamfer's Distance without SLAM
8	**2.1**	2.28
9	**1.58**	1.91
10	**3.69**	4.57
11	**3.01**	3.35
12	1.78	**1.31**
13	**3.11**	3.9
14	4.55	**3.92**

Comparison of Generative Modelling results with and without Diff. SLAM on CARLA-64

Conclusion

Differentiable SLAM helps deep learning based downstream perception tasks.

Restriction is that the output should be a per-point classification or regression task.

Integration of loop closure constraints is a promising future direction

Slam Error module is time consuming. Efficient implementation are required.

[1]Grad-Lidar-SLAM: Fully Differentiable Global SLAM for Lidar with Pose-Graph Optimization