3DSFLabelling: Boosting 3D Scene Flow Estimation by Pseudo Auto-labelling

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Task

➤ Auto-labelling of point-wise 3D motion fields.

Challenges addressed

➤ Reducing reliance on synthetic datasets, as models trained on synthetic data still exhibit poor generalizability to real-world scenarios.

➤ The scarcity of scene flow labels in actual driving scenarios, coupled with the significant difficulty of manually annotating 3D motion flows.

➤ The difficulty for existing 3D scene flow estimation networks to adapt to raw LiDAR data.

Contribution

➤ We propose a new framework for the automatic labelling of 3D scene flow pseudo-labels, significantly enhancing the accuracy of current scene flow estimation models, and effectively addressing the scarcity of 3D flow labels in autonomous driving.

➤ We propose a universal 3D box optimization method with multiple motion attributes. Building upon this, we further introduce a plug-and-play 3D scene flow augmentation module with global-local motions and motion status. This allows for flexible motion adjustment of ego-motion and dynamic environments, setting a new benchmark for flow data augmentation.

➤ Our method achieves state-of-the-art performance on KITTI, nuScenes, and Argoverse LiDAR datasets. Impressively, our approach surpasses all supervised and unsupervised methods without requiring any synthesising data and manual scene flow labels.
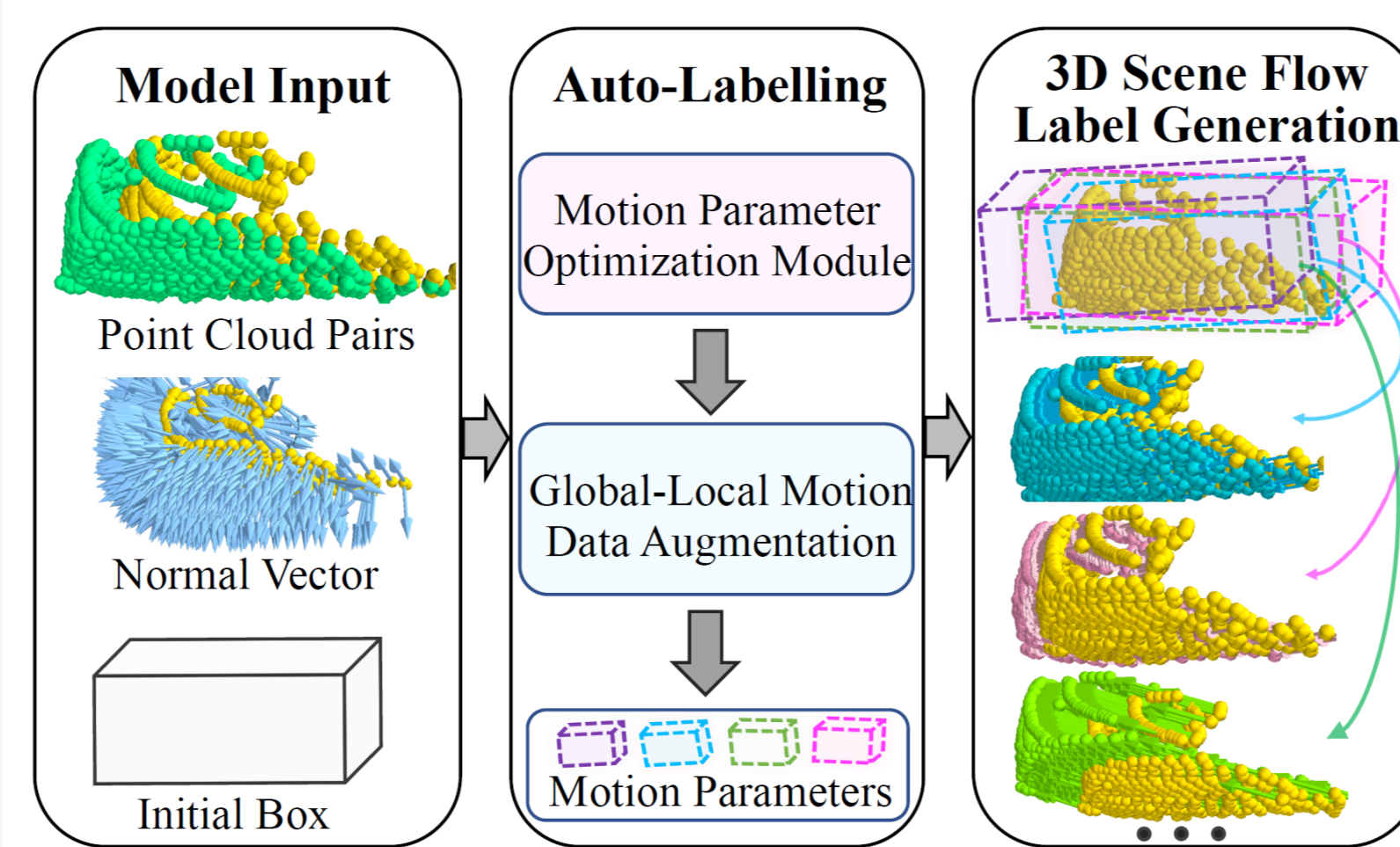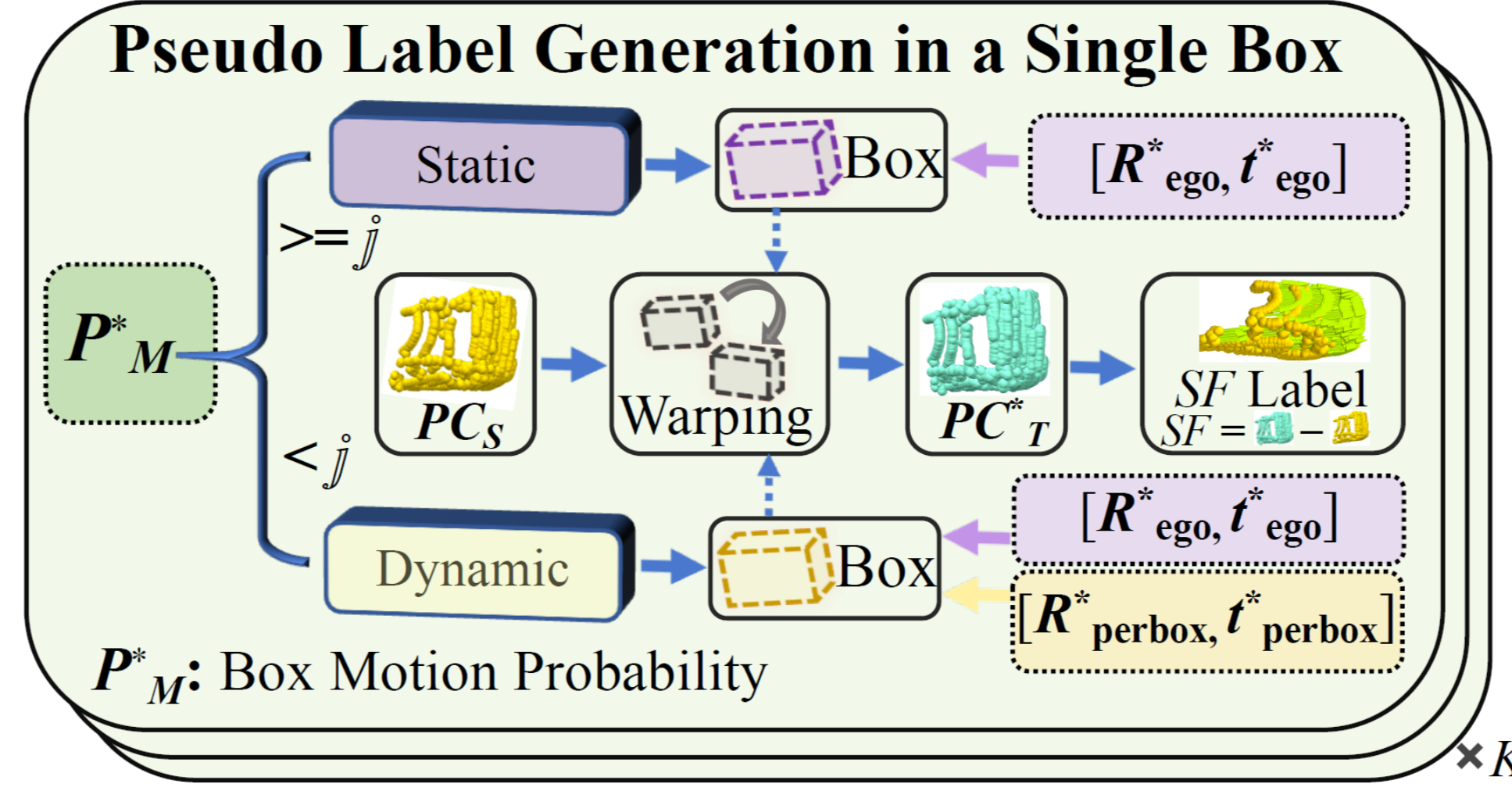
Competitive Performance
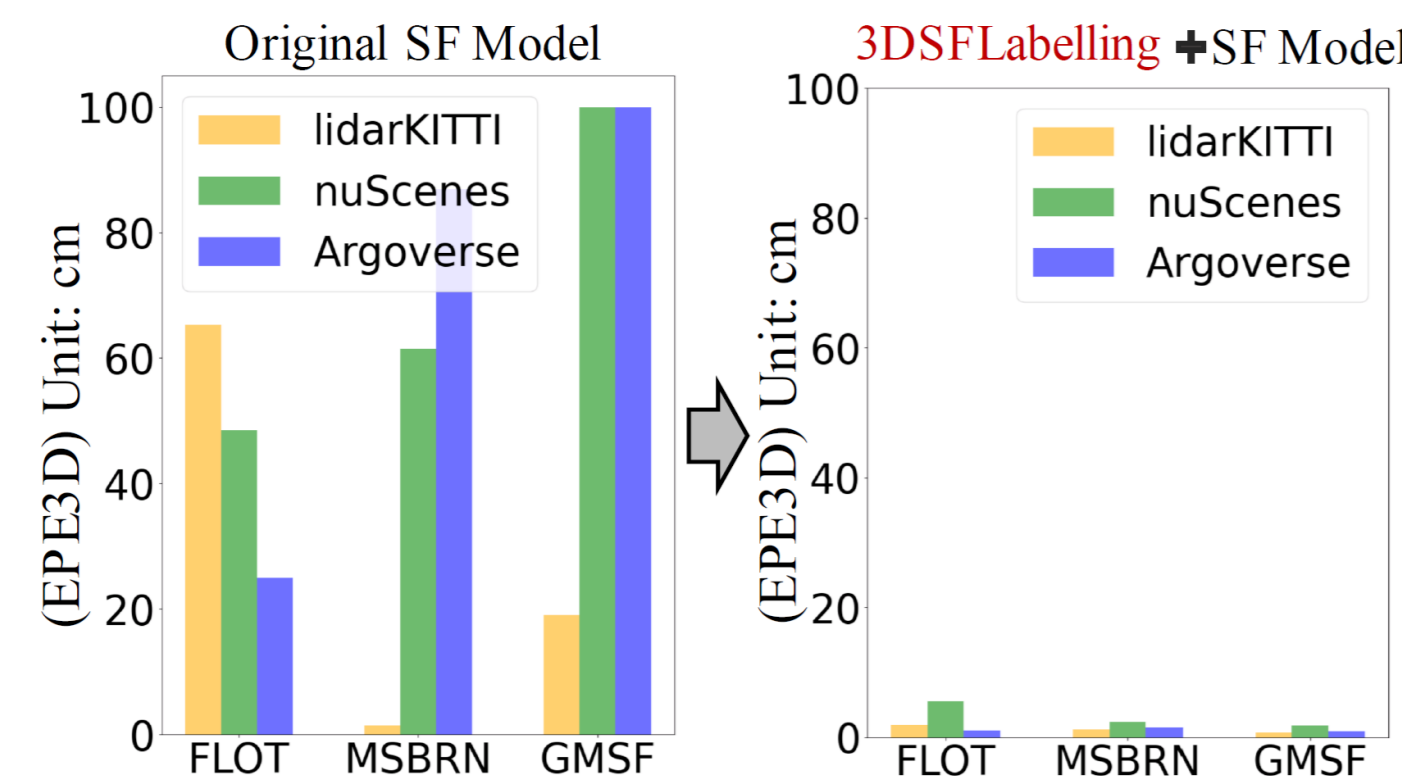
Architecture
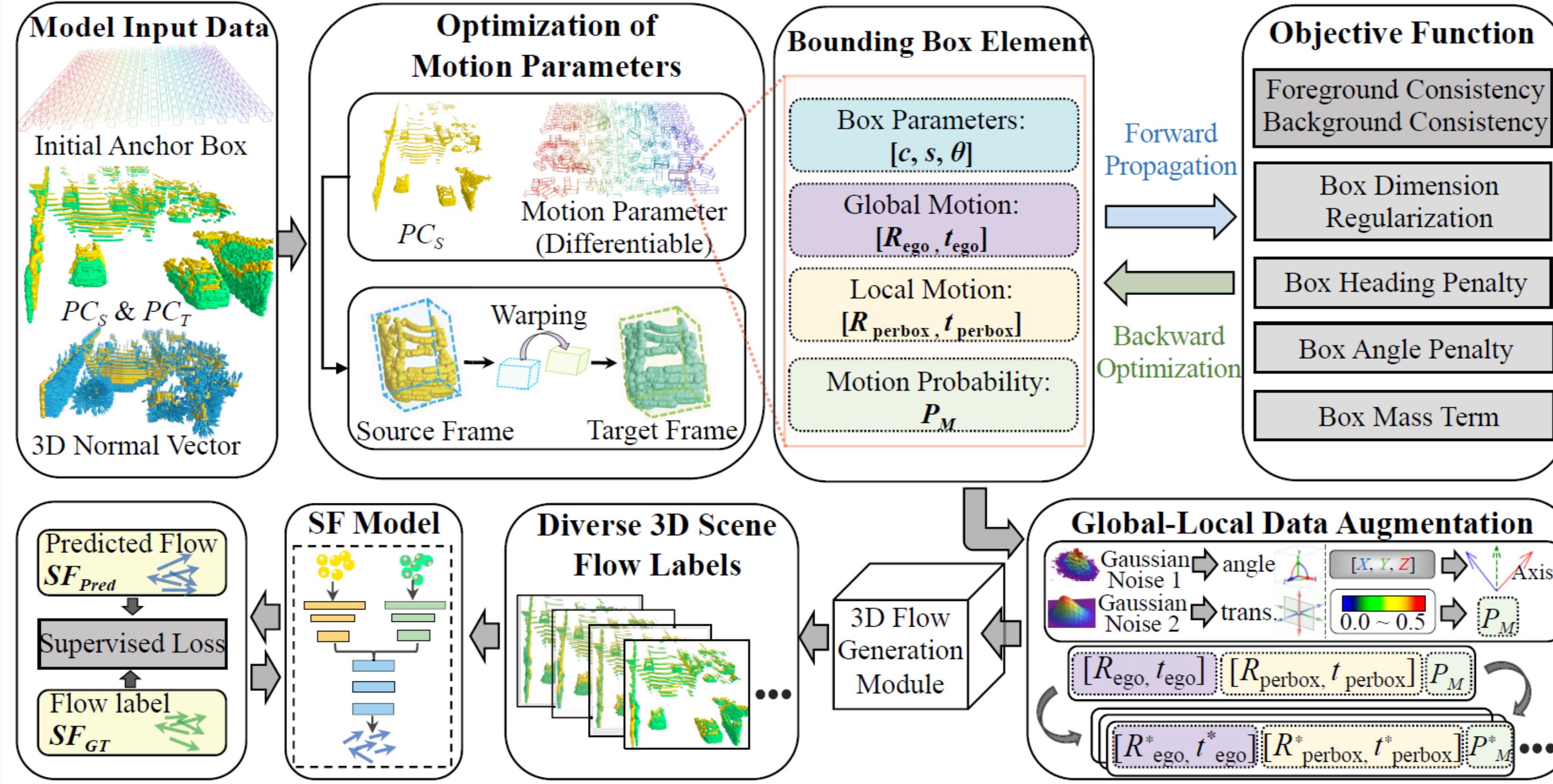
➤ **Auto-labelling Brief Framework**

➤ **Scene Flow Label Generation Module**

Quantitative experiment

Method	Sup.	LiDAR KITTI Scene Flow [10]				Argoverse Scene Flow [3]				nuScenes Scene Flow [2]			
		EPE3D↓	Acc3DS↑	Acc3DR↑	Outliers↓	EPE3D↓	Acc3DS↑	Acc3DR↑	Outliers↓	EPE3D↓	Acc3DS↑	Acc3DR↑	Outliers↓
Graph prior [35]	None	–	–	–	–	0.2570	0.2524	0.4760	–	0.2890	0.2012	0.4354	–
RSF [5]	None	0.0850	0.8830	0.9290	0.2390	–	–	–	–	0.1070	0.7170	0.8620	0.3210
NSFP [23]	None	0.1420	0.6880	0.8260	0.3850	0.1590	0.3843	0.6308	–	0.1751	0.3518	0.6345	0.5270
R3DSF [12]	Weak	0.0940	0.7840	0.8850	0.3140	0.4160	0.3452	0.4310	0.5580	–	–	–	–
FlowNet3D [28]	Full	0.7220	0.0300	0.1220	0.9650	0.4550	0.0134	0.0612	0.7360	0.5050	0.2120	0.1081	0.6200
PointPWC [49]	Full	0.3900	0.3870	0.5500	0.6530	0.4288	0.0462	0.2164	0.9199	0.7883	0.0287	0.1333	0.9410
DCA-SRSFE [18]	Full	0.5900	0.1505	0.3331	0.8485	0.7957	0.0712	0.1468	0.9799	0.7042	0.0538	0.1183	0.9766
FLOT [36]	Full	0.6532	0.1554	0.3130	0.8371	0.2491	0.0946	0.3126	0.8657	0.4858	0.0821	0.2669	0.8547
MSBRN [4]	Full	0.0139	0.9752	0.9847	0.6171	0.8691	0.2432	0.2854	0.7597	0.6137	0.2354	0.2924	0.7638
GMSF [51]	Full	0.1900	0.2962	0.5502	0.6171	7.2776	0.0036	0.0144	0.9930	9.4231	0.0034	0.0086	0.9943
Mittal et al. [32]	Self	0.9773	0.0096	0.0524	0.9936	0.6520	0.0319	0.1159	0.9621	0.8422	0.0289	0.1041	0.9615
Jiang et al. [17]	Self	0.4908	0.2052	0.4238	0.7286	0.2517	0.1236	0.3666	0.8114	0.4709	0.1034	0.3175	0.8191
Ours	Self	**0.0078**	**0.9924**	**0.9947**	**0.1328**	**0.0093**	**0.9780**	**0.9880**	**0.1302**	**0.0185**	**0.9534**	**0.9713**	**0.1670**

➤ Improvement on Baseline

Dataset	Method	EPE3D↓	Acc3DS↑	Acc3DR↑
LiDAR KITTI	FLOT [36]	0.6532	0.1554	0.3130
	FLOT+3DSFlabelling	**0.0189** ↑ 97.1%	0.9666	0.9792
	MSBRN [4]	0.0139	0.9752	0.9847
	MSBRN+3DSFlabelling	**0.0123** ↑ 11.5%	0.9797	0.9868
	GMSF [51]	0.1900	0.2962	0.5502
	GMSF+3DSFlabelling	**0.0078** ↑ 95.8%	0.9924	0.9947
Argoverse	FLOT [36]	0.2491	0.0946	0.3126
	FLOT+3DSFlabelling	**0.0107** ↑ 95.7%	0.9711	0.9862
	MSBRN [4]	0.8691	0.2432	0.2854
	MSBRN+3DSFlabelling	**0.0150** ↑ 98.3%	0.9482	0.9601
	GMSF [51]	7.2776	0.0036	0.0144
	GMSF+3DSFlabelling	**0.0093** ↑ 99.9%	0.9780	0.9880
nuScenes	FLOT [36]	0.4858	0.0821	0.2669
	FLOT+3DSFlabelling	**0.0554** ↑ 88.6%	0.7601	0.8909
	MSBRN [4]	0.6137	0.2354	0.2924
	MSBRN+3DSFlabelling	**0.0235** ↑ 96.2%	0.9413	0.9604
	GMSF [51]	9.4231	0.0034	0.0086
	GMSF+3DSFlabelling	**0.0185** ↑ 99.8%	0.9534	0.9713

➤ Model Comparison on Argoverse

By combining our auto-labelling framework with a very small parameter model FLOT, we have surpassed all methods.

Method	Sup.	EPE3D↓	Acc3DS↑	Acc3DR↑	Time↓	Params.↓
PointPWC [49]	Full	0.4288	0.0462	0.2164	147 ms	7.7 M
PV-RAFT [47]	Full	10.745	0.0200	0.0100	169 ms	–
R3DSF [12]	Weak	0.4160	0.3452	0.4310	113 ms	8.0 M
FlowStep3D [19]	Self	0.8450	0.0100	0.0800	729 ms	–
NSFP [23]	None	0.1590	0.3843	0.6308	2864 ms	–
Fast-NSF [24]	None	0.1180	0.6993	0.8355	124 ms	–
MBNSF [41]	None	0.0510	0.7936	0.9237	5000+ ms	–
MSBRN+3DSFlabelling	Self	0.0150	0.9482	0.9601	341 ms	3.5 M
GMSF+3DSFlabelling	Self	**0.0093**	**0.9780**	**0.9880**	251 ms	6.0 M
FLOT+3DSFlabelling	Self	0.0107	0.9711	0.9862	**78 ms**	**0.1 M**

Datasets	Method	Sup.	Training datasets	EPE3D↓	Acc3DS↑	Acc3DR↑	Outliers↓
	MBNSF [25]	None	None	0.0970	0.7415	0.8924	–
	Fast-NSF [16]	None	None	0.1060	0.7753	0.8899	–
	NSFP [15]	None	None	0.1380	0.5362	0.7857	–
	FLOT [23]	Full	FT3D	0.2908	0.0996	0.2459	0.8475
	MSBRN [3]	Full	FT3D	0.7534	0.2043	0.2844	0.8173
Waymo Open Scene Flow [24]	GMSF [32]	Full	FT3D	6.1888	0.0015	0.0063	0.9956
	GMSF [32]	Full	Waymo Open	0.0830	0.7470	0.8510	0.4350
	R3DSF [7]	Weak	FT3D + odKITTI	0.4140	0.3547	0.4496	–
	PointPWC [30]	Self	FT3D	4.1090	0.0005	0.0036	–
	FlowStep3D [11]	Self	FT3D	0.7530	0.0001	0.0009	–
	DCA-SRSFE [10]	Self	Waymo Open	0.0501	0.7482	0.9220	0.4088
	DCA-SRSFE [10]	Self	GTA-SF+Waymo Open	**0.0482**	0.7639	0.9253	0.3906
	Ours (FLOT+3DSFlabelling)	Self	FT3D + Argoverse (500)	0.0490	**0.7685**	**0.9264**	**0.3775**

Visualization