3D Perception & Learning Based Data Fusion

Multi-Modal Semantic Segmentation with Deep Learning based Data-Fusion

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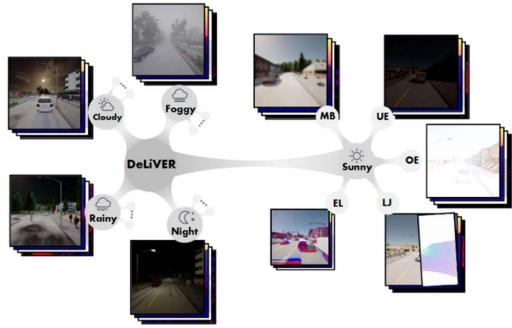
DATASET

• **DeLiver** is a really complex dataset, with 25 classes.

• Although the full dataset consists of **47310** samples for each sensor modality, only **7885** samples are publicly available.

• Split constists of 5988 training and 1897 testing samples.

- Contains images coming from **four different sensors**: RGB, Depth and Event cameras, plus LiDAR points projected onto 2D plane.
- Contains **four severe weather conditions** (cloudy, foggy, rainy and night), as well as **five sensor failures** (motion blur, over-exposure, under-exposure, LiDAR jitter and event low-resolution).





MODEL

SegFormer

• Powerful semantic segmentation framework which unifies Transformers with lightweight MLP decoder.

It has two main appealing features:

- A novel hierarchically structured Transformer encoder which outputs multiscale features.
- Avoids complex decoders, using a simple MLP decoder, which aggregates information from different layers.



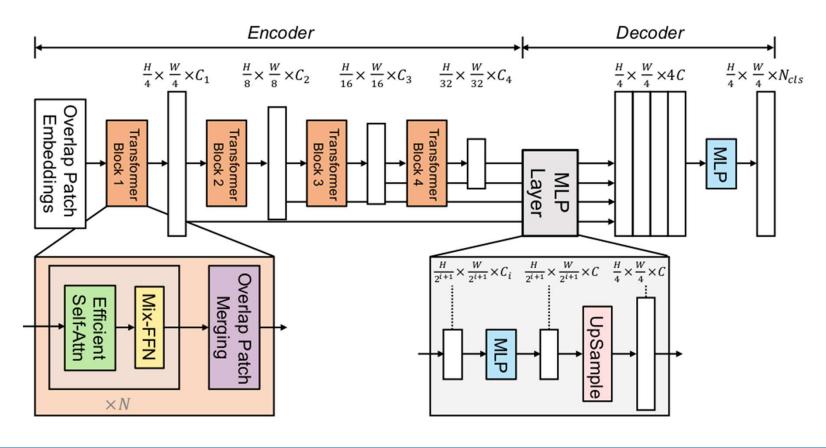
Does not need positional encoding, helpful when testing resolutions are different from training ones.



Allows to combine both local and global attention.



MODEL

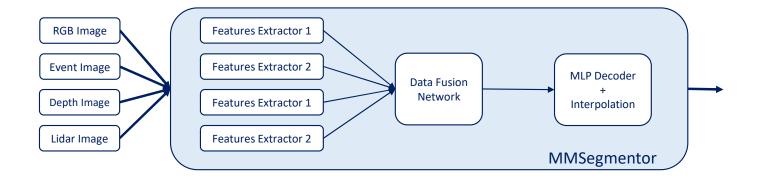




MODEL

Problem

- SegFormer does not support multimodality.
- We need to overload its architeture.

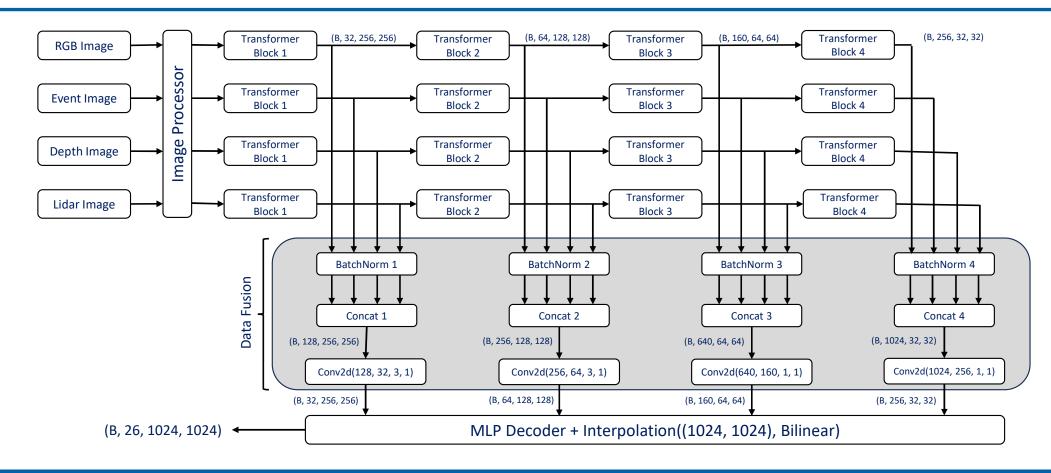


MMSegmentor

- The basic idea is to insert a deep learning data fusion architecture between the encoder and decoder.
- The final model is composed by four components:
 - 1. Feature Extractors: a total of four encoders, one for each modality;
 - 2. **Data-Fusion network**: four parallel combinations of batch normalization and 2D convolutional layers which acts on hidden states to fuse extracted features;
 - 3. MLP Decoder: takes fused hidden states as input and produces logits as output;
 - **4. Interpolator**: a simple bilinear interpolation layer which allows to upsample logits back to labels' required shape.



MODEL





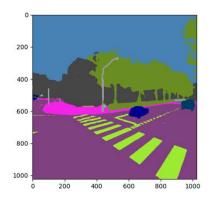
RESULTS

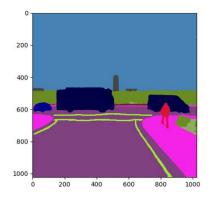
Model	mIoU (macro)	${f mIoU} \ {f (weighted)}$	Accuracy (macro)	Accuracy (weighted)			
DeepLabV3+ResNet50 NoAux PCA (Early-Fusion)	0.328	0.811	0.391	0.871			
DeepLabV3+ResNet101 NoAux PCA (Early-Fusion)	0.34	0.85	0.403	0.905			
MMSegmentor-B0	0.429	0.907	0.49	0.917			
MMSegmentor-B3	0.442	0.914	0.522	0.926			

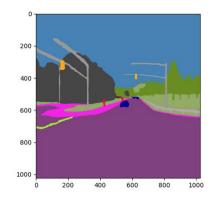
Model	Road		Sky		Building		Vegetation		RoadLine		Cars		SideWalk		Pedestrian		Pole		Truck	
Wiodei	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc
DeepLabV3																				
ResNet101	0.93	0.961	0.867	0.944	0.601	0.725	0.556	0.66	0.628	0.68	0.538	0.694	0.522	0.637	0.3	0.411	0.25	0.323	0.25	0.3
NoAux	0.95	0.901	0.007	0.944	0.001	0.725	0.550	0.00	0.028	0.08	0.556	0.094	0.322	0.037	0.5	0.411	0.25	0.323	0.25	0.5
RGB-Only																				
DeepLabV3																				
ResNet50	101												100				181		197.7	
NoAux	0.8997	0.9362	0.8992	0.965	0.6114	0.7297	0.4972	0.551	0.5955	0.6864	0.5424	0.616	0.5202	0.6757	0.3241	0.4152	0.2929	0.4485	0.2113	0.2754
PCA																				
Early-Fusion																				
DeepLabV3																				
ResNet101																				
NoAux	0.9389	0.9704	0.9259	0.9668	0.6386	0.7364	0.6159	0.7083	0.6097	0.6801	0.5688	0.7277	0.5518	0.7099	0.3434	0.4614	0.3018	0.4239	0.2431	0.2851
PCA																				
Early-Fusion																				
MMSegmentor-B0	0.9375	0.9651	0.9488	0.9826	0.6995	0.7797	0.6704	0.7736	0.5958	0.661	0.5707	0.737	0.5322	0.6664	0.4101	0.5134	0.2918	0.419	0.2279	0.2684
MMSegmento-B3	0.9556	0.975	0.9509	0.9833	0.7289	0.801	0.6979	0.7872	0.6012	0.672	0.5708	0.7377	0.5512	0.7003	0.4308	0.5192	0.3027	0.448	0.2339	0.271

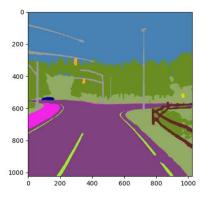


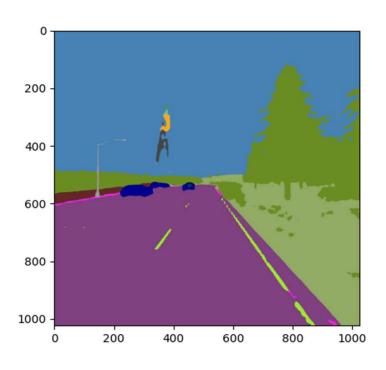
RESULTS

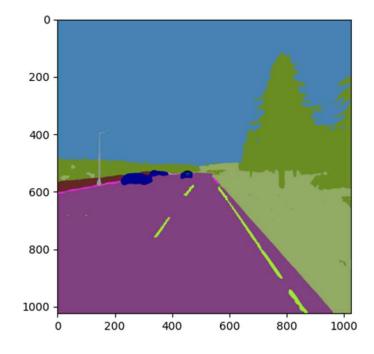














Thanks for the attention!