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## Efficient binary segmentation through dense neural networks in a truncated frequency domain

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## Context

Binary segmentation applied to robotics applications

- Used in robotics perception : classification of pixels of an image (into vehicles, road, pedestrians, etc.) or points of a point cloud
- **Real-time** execution on **resources-constrained** embedded chips

## State Of The Art

Typical Artificial Neural Networks (ANNs) for binary segmentation use **CNNs** directly inferred on images (U-Net [1]) or on a 2D projection of a LiDAR point cloud (VoxNet [2], RangeNet++ [3])

- **Computationally expensive** due to the size of the input tensor

**Frequency transformation** is used to enrich the input of ANNs, but also for image translation [4] and manipulation [5] in multimodal neural networks

- It is **not used to predict frequency domain output, nor to reduce the costs**

## Objective

Binary segmentation under the following constraints

- **Reduction of computational costs** in order to envision an integration into embedded resource constrained hardware in the future
- **Fully configurable** method regarding the available **computational resources**

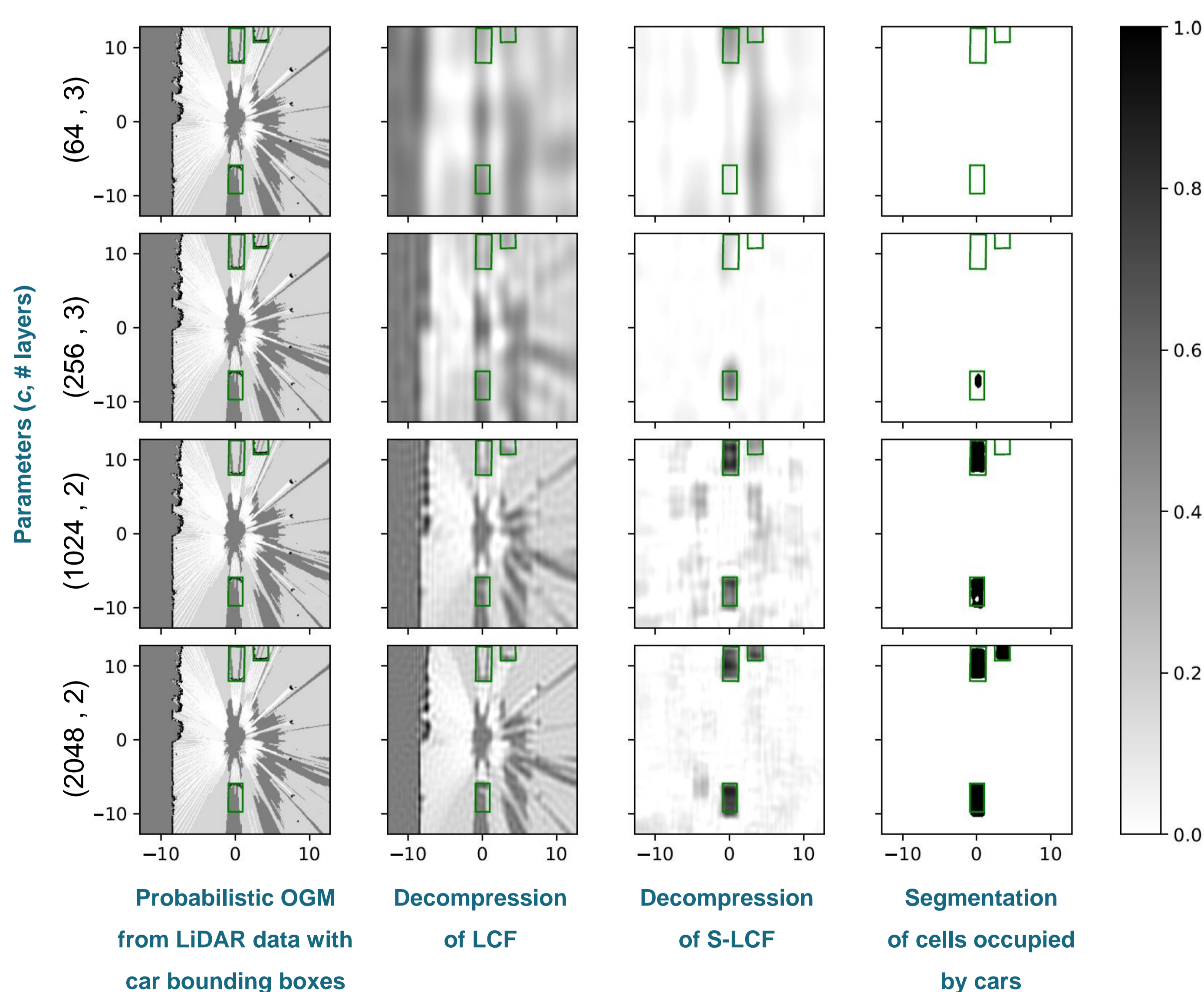
## Use-case : Binary Segmentation of OGM

**Probabilistic Occupancy Grid Map (OGM) [6]**

- Representation of the environment around a car into a bird's eye view image composed of 65,536 squared cells of size 10 cm x 10 cm
- A probability value between 0 and 1 estimates the confidence about the occupancy state of each cell

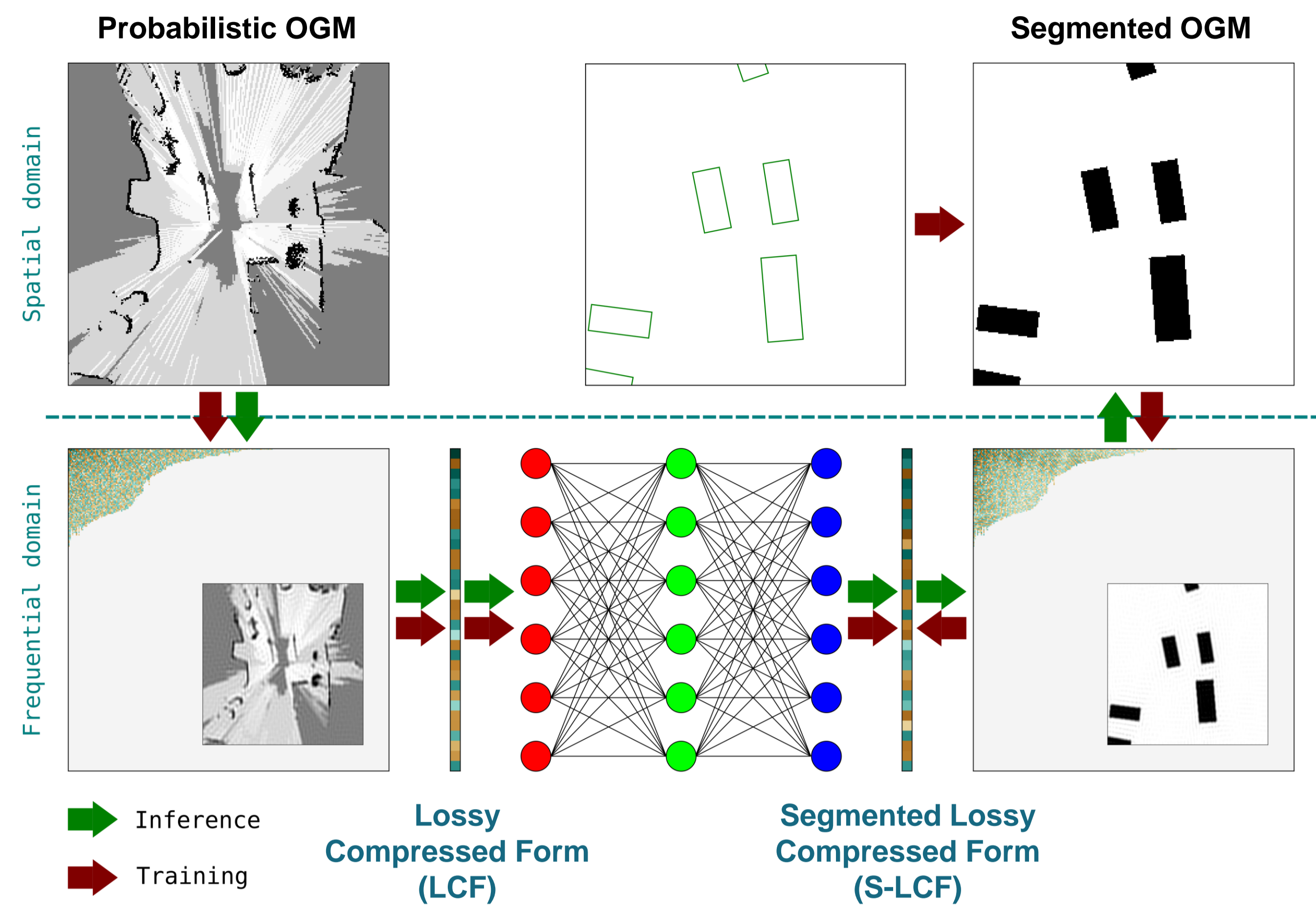
**Objective** : Segmentation of cells occupied by cars (binary segmentation)

**Dataset** : Original and segmented OGMs built from the bounding boxes of the labelled cars within the Waymo Open [7] dataset containing 198,068 traffic scenes



[1] Ronneberger et al. "U-Net: Convolutional Networks for Biomedical Image Segmentation"  
 [2] Maturana et al. "VoxNet: A 3D Convolutional Neural Network for real-time object recognition"  
 [3] Milioto et al. "RangeNet++: Fast and Accurate LiDAR Semantic Segmentation"  
 [4] Cai et al. "Frequency Domain Image Translation: More Photo-realistic, Better Identity-preserving"  
 [5] Li et al. "Image Manipulation Localization Using Attentional Cross-Domain CNN Features"  
 [6] Elfes "Using occupancy grids for mobile robot perception and navigation"  
 [7] Sun et al. "Scalability in Perception for Autonomous Driving: Waymo Open Dataset"

## Methodology



### Step #1 - Compression into Frequency Domain

**Input** : Probabilistic Occupancy Grid Map (OGM)

1. Transformation of OGM into its spectrum obtained by the **Discrete Cosine Transform (DCT)**
2. **Truncation** of the obtained spectrum via an optimal mask (learnt based on the training set) in order to select and **keep only c number of frequencies**, where  $c < \text{number of OGM cells}$
3. Flattening of the truncated spectrum into a 1D array

**Output** : **Lossy Compressed Form (LCF)** in the form of 1D array of size  $c$  containing the spectrum coefficients relative to the selected frequencies

### Step #2 - Segmentation of Compressed Input

**Input**: Lossy Compressed Form (LCF)

1. Use **ANN to generate a Segmented Lossy Compressed Form (S-LCF)**
  - Architecture : 2 or 3 dense layers of  $c$  neurons, with ReLU activation function for all layers except for the last one
  - Training : Adam optimizer with early stopping
2. **Decompression** of S-LCF into spatial domain
3. Binary segmentation of the decompressed form by thresholding

**Output**: Binary OGM where cells occupied by cars are segmented

## Experimental Results

Parameters		Quality	Computational costs	
$c$	# layers	AP	Time	# weights
64	2	0.272	0.76ms	8,320
64	3	0.280	0.77ms	12,480
128	2	0.337	0.84ms	33,024
128	3	0.405	0.91ms	49,536
256	2	0.456	0.83ms	131,584
256	3	0.484	0.88ms	197,376
512	2	0.531	0.85ms	525,312
512	3	0.530	0.92ms	787,968
1024	2	0.561	0.90ms	2,099,200
1024	3	0.536	1.04ms	3,148,800
2048	2	0.574	1.62ms	8,392,704
2048	3	0.527	2.16ms	12,589,056

- Quantitative results : **Inference times**  $< 2$  ms for **Average Precision (AP)**  $> 0.5$ , starting with compression parameter  $c \geq 512$  (compression ratios ranging from 1/128 to 1/32)
- Qualitative results show an ability of the neural networks to **segment properly** OGMs even under very degraded compressed forms