GPU TECHNOLOGY CONFERENCE

March 17 - 21, 2019 | San Jose McEnery Convention Center

APOSTERA

S9169 Augmented Reality Solution for Advanced Driver Assistance

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Agenda

- Company Introduction
- System Concept
- Perception Concept
- Object Detection DNN Showcase
- HMI Concept

Company Introduction

Company Introduction

- Unique augmented reality in the vehicle
- Ultimately easy and safe driving
- Full visibility of autonomous driving decisions

APOSTERA

- Headquarters in Munich
- Development centers in Eastern Europe, presence in Asia
- 50+ experienced and talented engineers in 4 countries
- 10+ years of automotive experience
- Know-how in core automotive domains: Vehicle Infotainment, Vehicle Sensors and Networks, Telematics, Advanced Driver Assistance Systems, Navigation and Maps,
- Collaboration with scientific groups in fields of Computer Vision and Machine Learning, unique IP and mathematical talents

Representation For The Driver

LCD screen

Past

Smart Glasses

Alternative,
fast developing market (today)

HUD 2D

Today

Real-depth HUD with wide FOV in car

On going development (2 years)

Technology

Recognition and Tracking

- Road boundaries and lane detection
- Slopes estimation
- Vehicle recognition and tracking
- Distance & time to collision estimation
- Pedestrian detection and tracking
- Facade recognition and texture extraction
- Road signs recognition

Integration with HD Maps

- HD Maps utilization for Precise positioning, Map matching and Path planning, Junction assistance
- Data generation for HD Maps

Computer Vision Approaches

- Real-time objects extraction from video sensors
- Road scene semantic segmentation
- Adaptability and output data confidence estimation
- GPU optimization for different platforms

Augmented Reality

- LCD, HUD & further output devices
- Natural navigation hints & infographics
- Collison, Lane departure, Blind spots warnings, etc.
- POIs and supportive information (facades and parking slots highlighting, etc.)

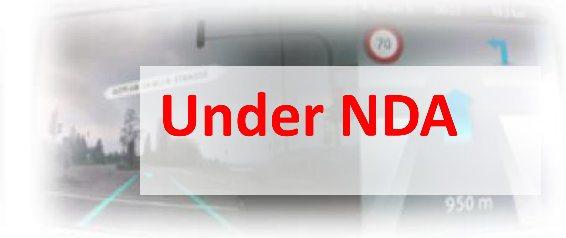
Sensor Fusion

- Flexible fusion of data from internal and external sources
- LIDAR data merging
- 3D-environment model reconstruction based on different sensors
- Latency compensation & data extrapolation

Machine Learning Specifics

- CNN and DNN approaches
- Supervised MRF parameters adjustment
- CSP-based structure & parameters adjustment (both supervised and unsupervised)
- Weak classifiers boosting & others

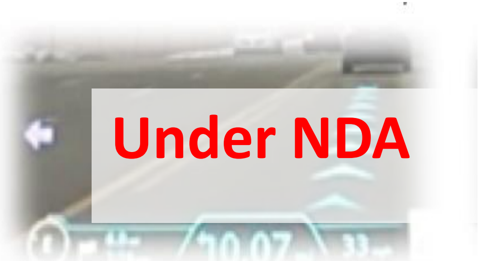
Reference Projects



AR LCD Prototype German OEM

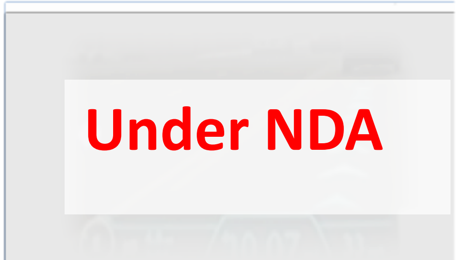
AR LCD Prototype BMW demo car

AR LCD CES Demo



AR HUD Prototype American OEM

AR HUD Prototype Shanghai OEM



AR Production Project
Premium OEM – ongoing

Challenges of ADAS embedded platforms

- ***Power*** vs ***Performance***
  - Focus on performance while presuming the low power consumption
- ***Low latency*** and ***High response frequency***
  - Fast responses to environment changes are crucial for working in real-time
- ***Robustness*** and ***Quality***
  - Ensure robustness and presume quality in difficult operating conditions
  - Requires a lot of verification scenarios as well as adaptive heuristics
- System architecture specifics for embedded ***real-time***
  - Designed for real-time requirements and portability to fit to most effective hardware platforms
- Hardware and software ***sensor fusion***
  - Fuse available data sources (sensors, maps, etc.) for robustness and quality
- ***Big data analysis***
  - Huge amount of data should be stored and used for development and testing
- In- and Off-field ***automated testing***
  - Adaptive heuristics development
  - System validation
  - Collecting special cases

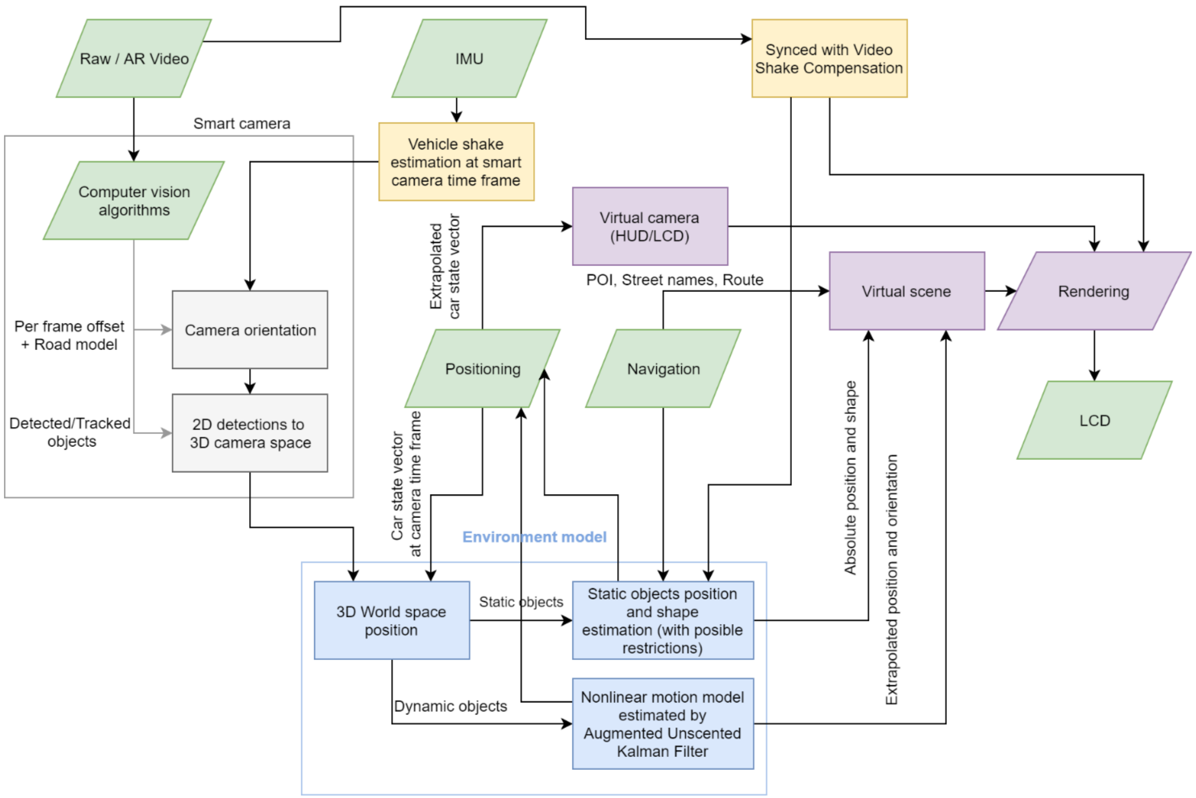
Challenges of ADAS machine learning

- Machine Learning needs large volumes of quality ***data***
  - Real need to ensure greater stability and accuracy in ML
  - High volumes of data might not be available for some tasks, limiting ML's adoption
- AI vs ***Expectations***
  - Understanding the limits of technology
  - Address expectations of replacing human jobs
- Becoming ***production-ready***
  - Transition from modeling to releasing production-grade AI solutions
- Current ML doesn't understand ***context*** well
  - Increased demand for real-time local data analysis
  - A need to quickly retrain ML models to understand new data
- Machine Learning ***security***
  - Addressing security concerns such as informational integrity

System Concept

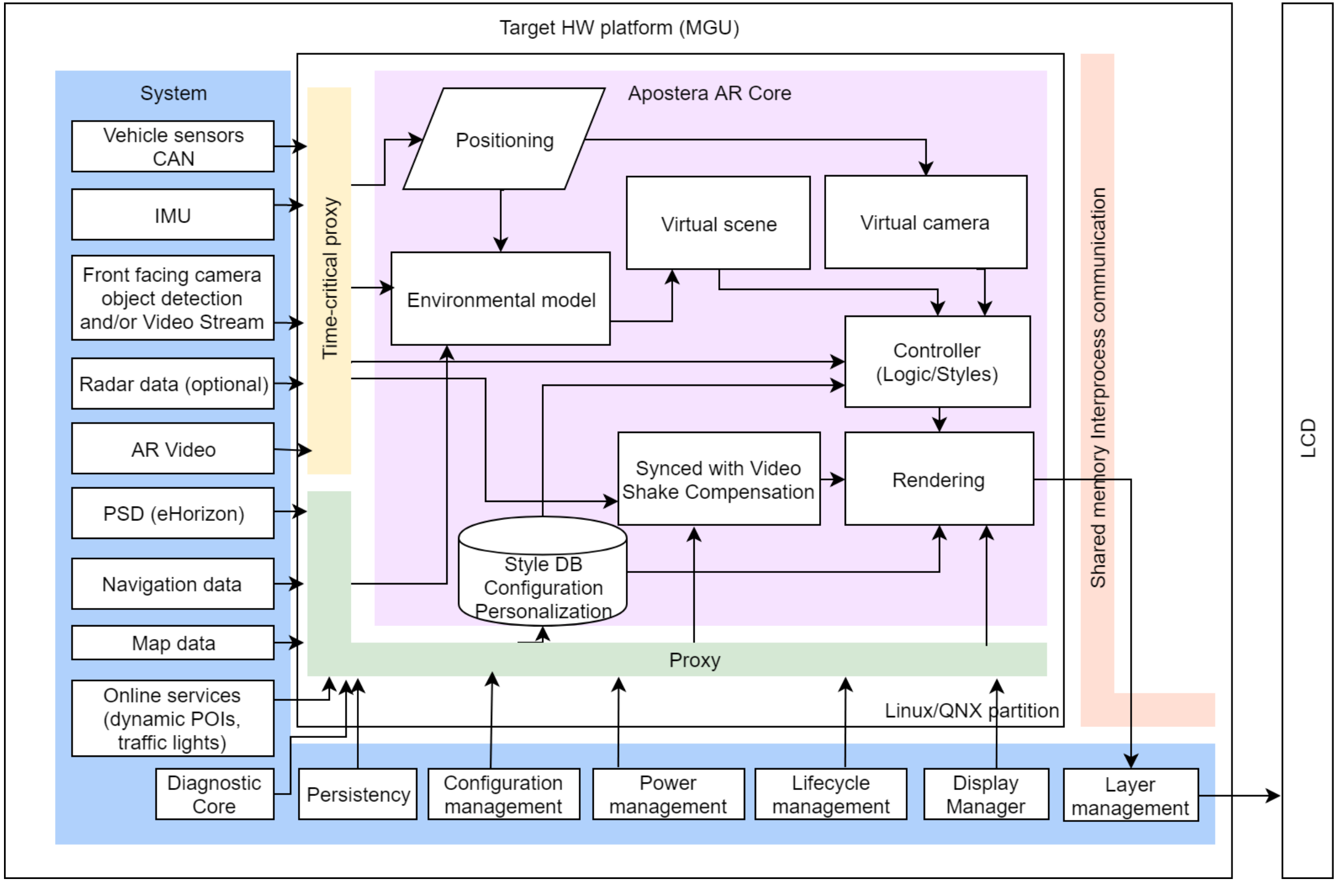
Apostera Approach – High Level & Highlights

- Hardware and sensors agnostic
- Confidence estimation of fusion/visualization
- Real-time with low resource consumption
- Latency compensation and prediction model
  - Pitch, roll, low- and high-frequency
- Configurable design for different OEMs
- Configurable logic requirements (including models and regions)
  - User interface logic considers confidence or probability of input data
  - Considers the dynamic environment and objects occlusion logic
- Integration with different navigation systems and map formats
  - Compensation of map data inaccuracy
  - Precise relative and absolute positioning



Apostera Solution Architecture Overview

High-level True Augmented Reality Solution overview: In-vehicle functioning mode



Cameras. Transport and Sensors

ADAS camera challenges

Low latency	Demand for algorithms reaction time Resolving data source synchronization issue
Small footprint	Demand for increasing number of ADAS sensors Increasingly space constrained
Low power	Reduced heat improves image quality & reliability Battery applications
High Reliability	Harsh environment Passenger and industrial vehicles

IP / ETH AVB / GMSL transport comparison

Frame exposure (33 ms)	encoder (1 ms)	IP transmit (70 ms)	decoder (1 ms)	~105ms
Frame exposure (33 ms)	Encoder (1 ms)	ETH AVB (2 ms)	decoder (1 ms)	~37ms
line exposure (45µs)	serializer	LVDS	deserializer	~33ms

15µs (per line)

Supplier Type		Aptina AR0130	Aptina AR0231	Omnivision OV 10635
Resolution	pixel	1280x960	1928x1208	1280x800
Dynamic	dB	115 (HDR)	120(HDR)	115(HDR)
Response	V/L-sec	5.48	-	3.65
Frames	fps	60	40	30
Shutter Type	GS/ERS	ERS	ERS	ERS
Sensor optical format	Inch (“)	1/3”	1/2.7”	1/2.7”
Pixel size	µm	3.75	3	4.2
Interface		Parallel RGB	MIPI CSI2	Parallel DVP
Application		ADAS	ADAS	ADAS
Operation temp.	°C	-40...+105	-40...+105	-40...+105

Table – camera sensors comparison

Perception Concept

Sensor Fusion. Data Inference

Optimal fusion filter parameters adjustment problem statement and solution developed to fit different car models with different chassis geometries and steering wheel models/parameters.

Features:

- Absolute and relative positioning
- Dead reckoning
- Fusion with available automotive grade sensors – GPS, steering wheel, steering wheel rate, wheels sensors
- Fusion with navigation data
- Rear movements support
- Complex steering wheel models identification. Ability to integrate with provided models
- GPS errors correction
- Stability and robustness against complex conditions – tunnels, urban canyons

Sensor Fusion. Advanced Augmented Objects Positioning

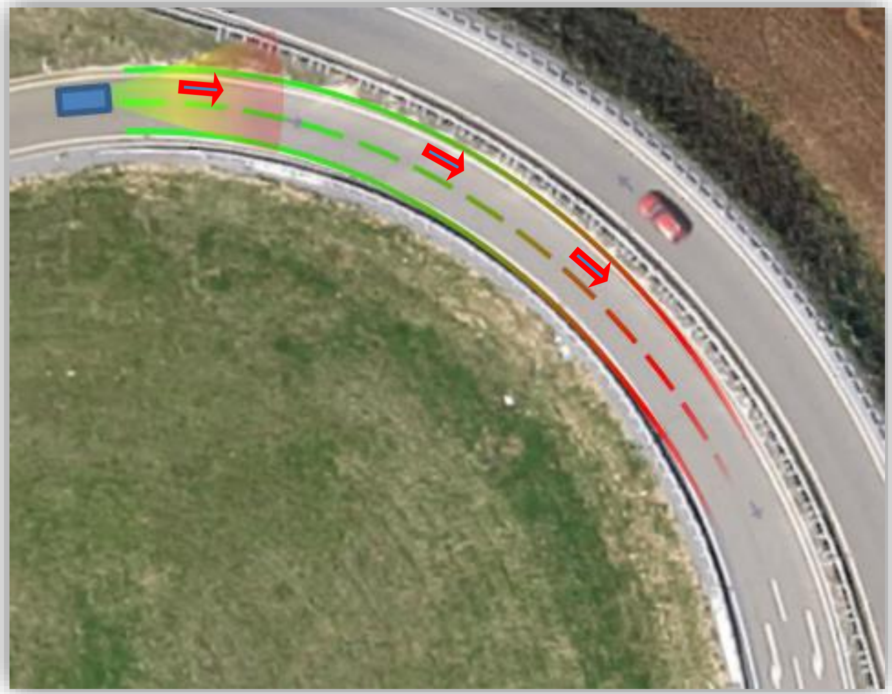
- Solving map accuracy problems

Placing:

- Road model
- Vehicles detection
- Map data

Position clarification:

- Camera motion model:
  - Video-based gyroscope
  - Positioner Component
- Road model
- Objects tracking



Sensor Fusion. Comparing Solutions

Apostera solution

Update frequency ~15 Hz (+extrapolation with any fps)

Reference solution

Update frequency ~4-5 Hz

Lane Detection. Adaptability and Confidence

- Low level invariant features
  - Single camera
  - Stereo data
  - Point clouds
- Structural analysis
- Probabilistic models
  - Real-world features
  - Physical objects
  - 3D scene reconstruction
  - Road situation
- 3D space scene fusion (different sensors input)
- Backward knowledge propagation from environment model

Ongoing work. More detection classes

- Road object classes extension
  (without a loss of quality for existing classes)
  - Adding traffic signs recognition (detector + classifier)
  - Adding traffic lights recognition

Ongoing work. Drivable area detection

- Drivable area detection using semantic segmentation
- Model is inspired by Squeeze-net and U-Net.
- Current performance (Jetson TX2):
  - Input size: 640x320 (lowres)
  - Inference speed: 75 ms/frame

Object Detection DNN Showcase

Object detection DNNs. Speed vs Accuracy

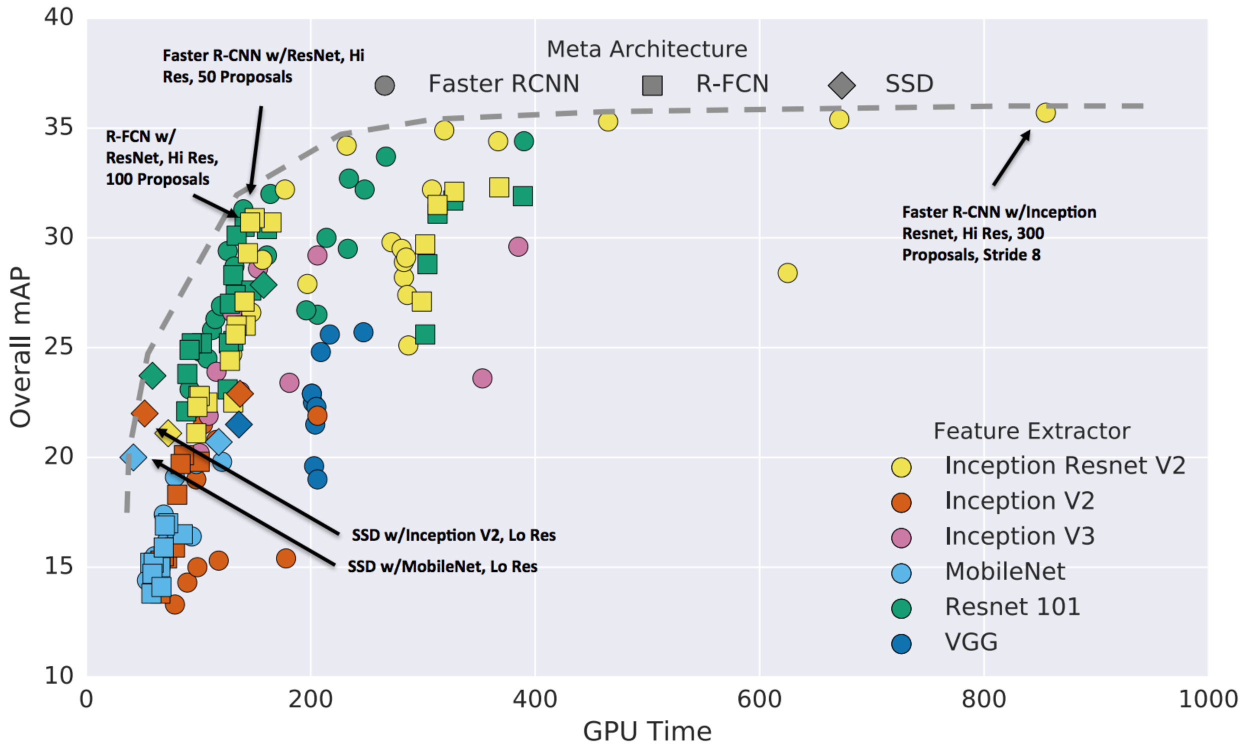


Figure – Accuracy (mAP) vs inference time of different meta architecture / feature extractor combinations for MS COCO dataset

Single Shot Multibox Detector

- Discretizes the output space of bounding boxes into a set of default boxes over different aspect ratios and scales per feature map location
- Generates scores for the presence of each object category in each default box and produces adjustments to the box to better match the object shape
- Combines predictions from multiple feature maps with different resolutions to handle various sizes
- Simple relative to methods that require object proposals, eliminates proposal generation and subsequent pixel or feature resampling stages, encapsulates all computation in a single network

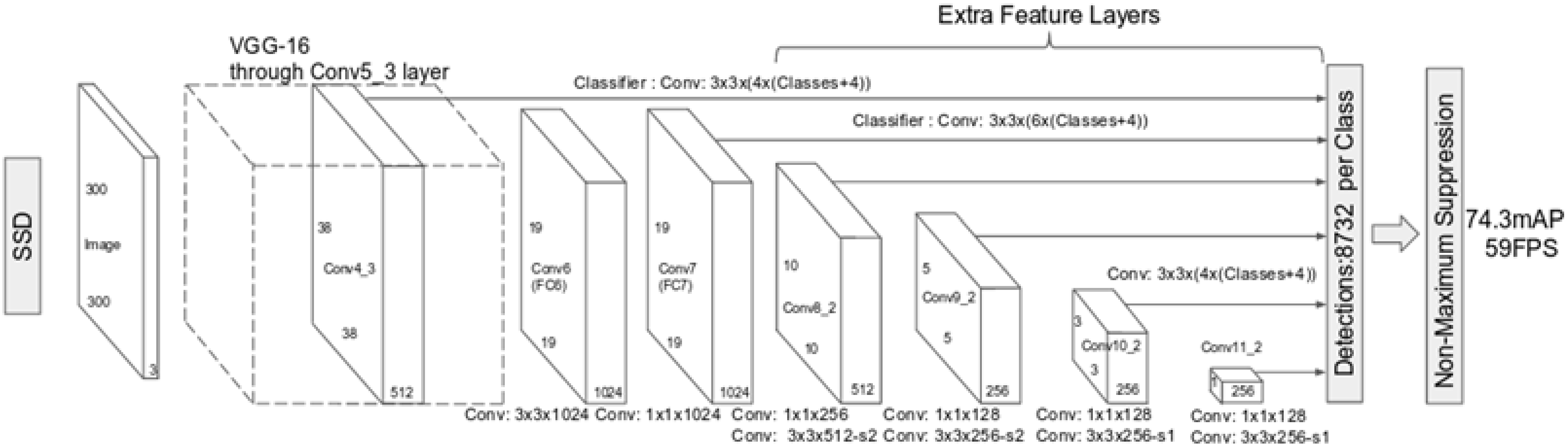
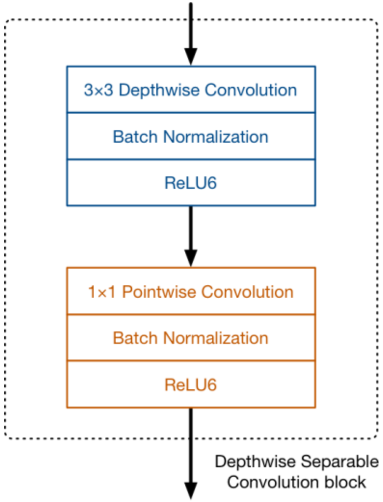


Figure – SSD model architecture

MobileNet as a Feature Extractor

- Depth wise separable convolutions to build light weight deep neural networks
- Two global hyper parameters to adjust between latency and accuracy
- Solid performance compared to other popular models on ImageNet classification
- Effective across a wide range of applications and use cases:
  - object detection
  - fine grain classification
  - face attributes
  - large scale geo-localization



Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

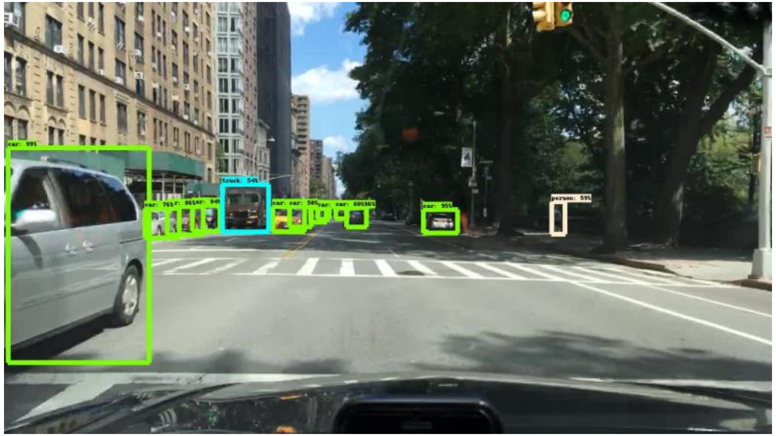
Figure - Depth wise separable convolution block and MobileNet architecture

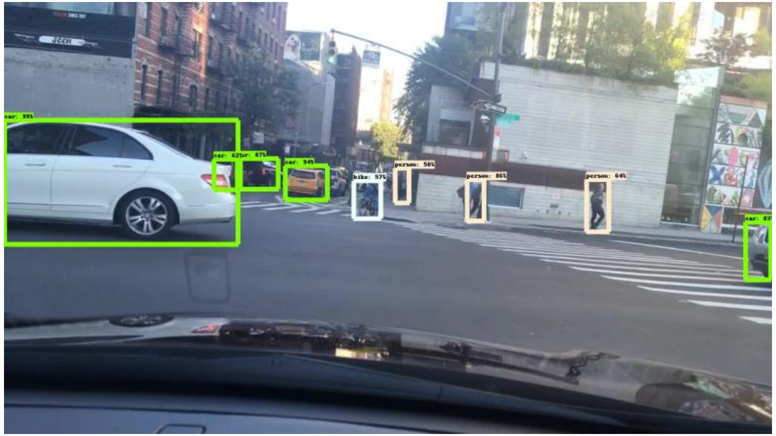
SSD-MobileNet Qualities

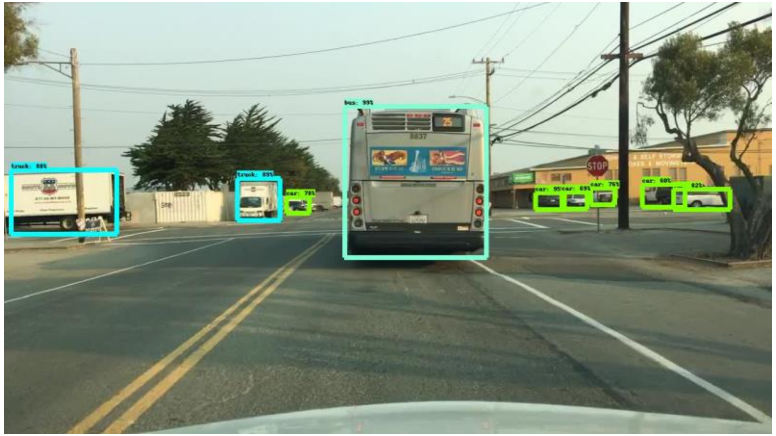
- Speed vs Accuracy:
  - SSD with MobileNet has the highest mAP among the models targeted for real-time processing
- Feature extractor:
  - The accuracy of the feature extractor impacts the detector accuracy, but it is less significant with SSD.
- Object size:
  - For large objects, SSD performs pretty well even with a simple extractor. SSD can even match other detectors' accuracies using better extractor. But SSD performs worse on small objects compared to other methods.
- Input image resolution
  - Higher resolution improves object detection for small objects significantly while also helping large objects. Decreasing resolution by 2x in both dimensions lowers accuracy, but with 3x reduced inference time.
- Memory usage
  - MobileNet has the smallest RAM footprint. It requires less than 1Gb (total) memory.

SSD-MobileNet Detection Quality

- Input size: 640x360
- Detection quality for classes (AP@0.5IOU):
  - Light vehicle – 0.52
  - Truck/bus – 0.36
  - Cyclist/motorcyclist – 0.255
  - Pedestrian – 0.29







SSD-MobileNet. Basic Inference Performance

Desktop platform (PC)

- Quad-core Intel Core i5-7400
- 16 GB DDR4
- GeForce GTX 1060 (6 Gb)
- CUDA 8.0, CuDNN 6, TensorFlow v1.5

Reference platform – ***NVIDIA Jetson TX2***

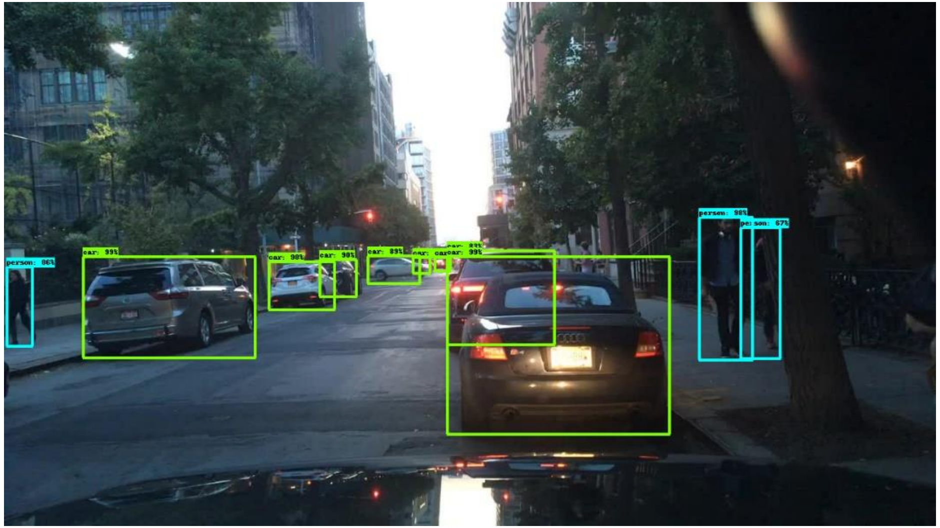
- Dual-core NVIDIA Denver2
- Quad-core ARM Cortex-A57
- 8GB 128-bit LPDDR4
- 256-core Pascal GPU (max freq)
- CUDA 8.0, CuDNN 6, TensorFlow v1.5

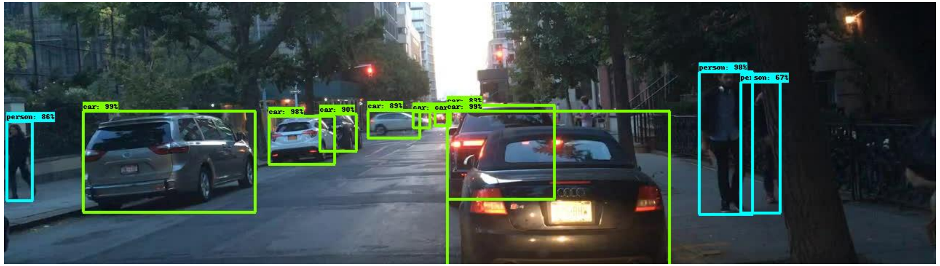
Input image resolution	PC GPU inference (ms/frame)	TX2 GPU inference (ms/frame)
1280x720	*49.55*	*185.0*
853x480	*26.3*	*84.87*
640x360	*15.7*	*56.21*
427x240	*8.25*	*32.51*

Table – Inference performance

Inference Optimization. ROI

- **Challenge**: reducing input horizontal resolution under 640p resulted in serious decrease of narrow object accuracy (e.g. pedestrians)
- **Solution**: reduce ROI further only by height, remove small objects from training
  - Most road objects occupy center half of the frame
  - Use dynamic frame crop by horizon level
  - SSD can deal with truncated/occluded close objects





Inference Optimization. Model depth

- MobileNet provides two hyper parameters:
  - width multiplier, resolution multiplier
- The role of the width multiplier α is to thin a network uniformly at each layer
- **Solution**: decrease the width multiplier to thin the network and remove redundant convolutions
  - Width multiplier **0.75** was chosen for current road objects dataset

Width Multiplier (alpha)	ImageNet Acc (%)	Multiply-Adds (M)	Params (M)
1.0 MobileNet-224	*70.6*	*529*	*4.2*
0.75 MobileNet-224	*68.4*	*325*	*2.6*
0.50 MobileNet-224	*63.7*	*149*	*1.3*
0.25 MobileNet-224	*50.6*	*41*	*0.5*

Table – MobileNet accuracy vs width multiplier on ImageNet dataset

Inference Optimization. Runtime

- Runtime and driver update
  - From: CUDA 8.0 + cuDNN 6
  - To: CUDA 9.0 + cuDNN 7
- Utilizing low level optimization efforts from specialized libraries
- Performance upgrade at low development cost

Input image resolution	TX2 CUDA 8 (ms/frame)	TX2 CUDA 9 (ms/frame)	Speedup
640x360	*56.2*	*54.5*	***+3.1%***

Table – Runtime performance comparison

SSD-MobileNet. Optimized Performance

- Input size: 640x360
- Detection quality for classes (AP@0.5IOU):
  - Vehicle – 0.52
  - Pedestrian – 0.288

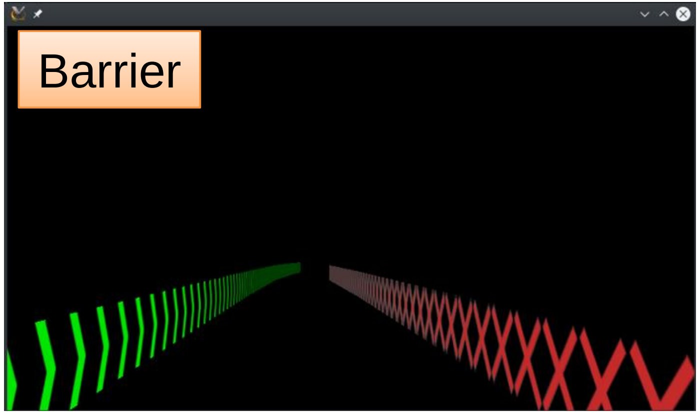
- New input size: 640x180
- Width multiplier: 0.75
- Detection quality for classes (AP@0.5IOU):
  - Vehicle – 0.6891 (***small obj removed***)
  - Pedestrian – 0.2902

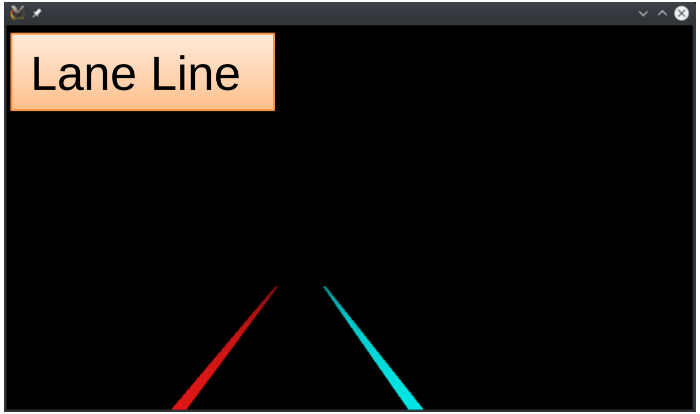
Input image resolution	Width Multiplier (alpha)	TX2 CPU inference (ms/frame)	TX2 GPU inference (ms/frame)	CPU/GPU speedup
640x360	*1.0*	*262*	*56.2*	*4.66x*
640x180	*0.75*	*115.5*	***30.3***	*3.81x*

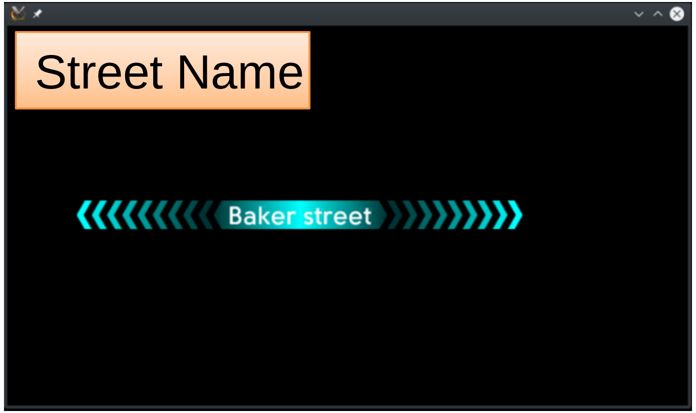
Table – Final performance comparison

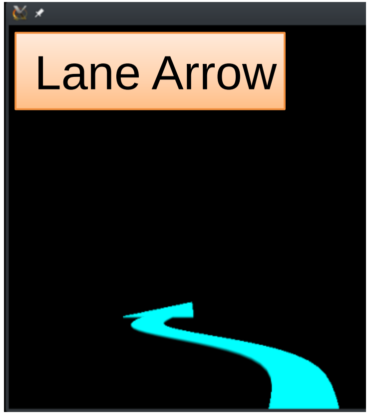
HMI Concept

Augmented Objects Primitives





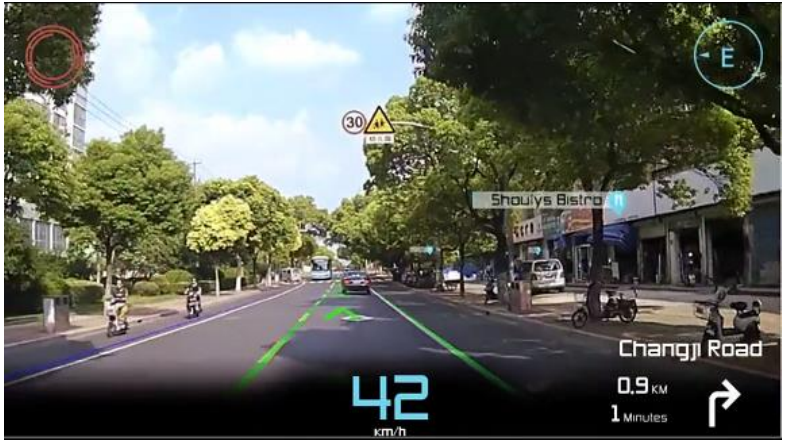




Augmented Objects Primitives and HMI

HUD vs LCD. Overview

- Hardware limitation
  - HUD devices are rarely available on market
  - FOV and object size
- Timings
  - Zero latency
  - Driver eye position
- Driver perception
  - Virtual image distance
  - Information balance



HUD vs LCD. Navigation Features

Feature	LCD design	HUD design
Maneuver assistance		
Augmented POI and street name highlighting		

HUD vs LCD. ADAS Features

Feature	LCD design	HUD design
Forward Collision Warning		
Lane Departure Warning		

HUD Image Correction (Dewarping)

- System needs to correct a slight distortion in the HUD image
- A custom warp map is made by taking an image of a test pattern that was projected by the HUD and recorded by a camera

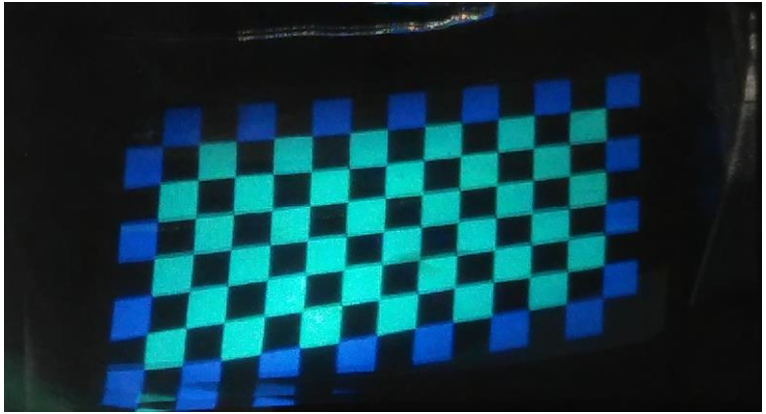


Figure – Uncorrected image

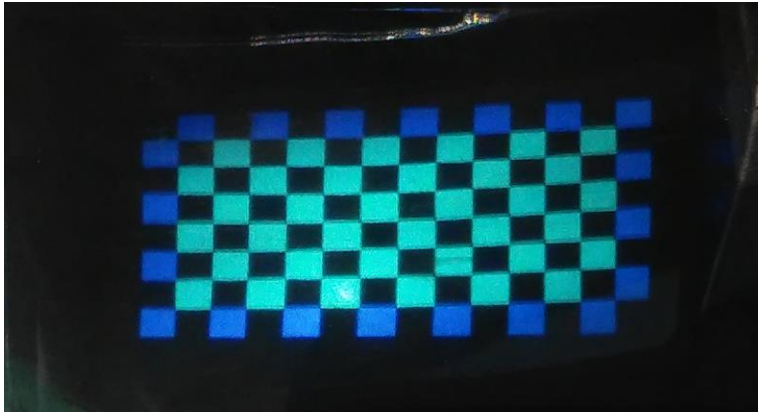


Figure – Corrected image

Rendering Component Structure

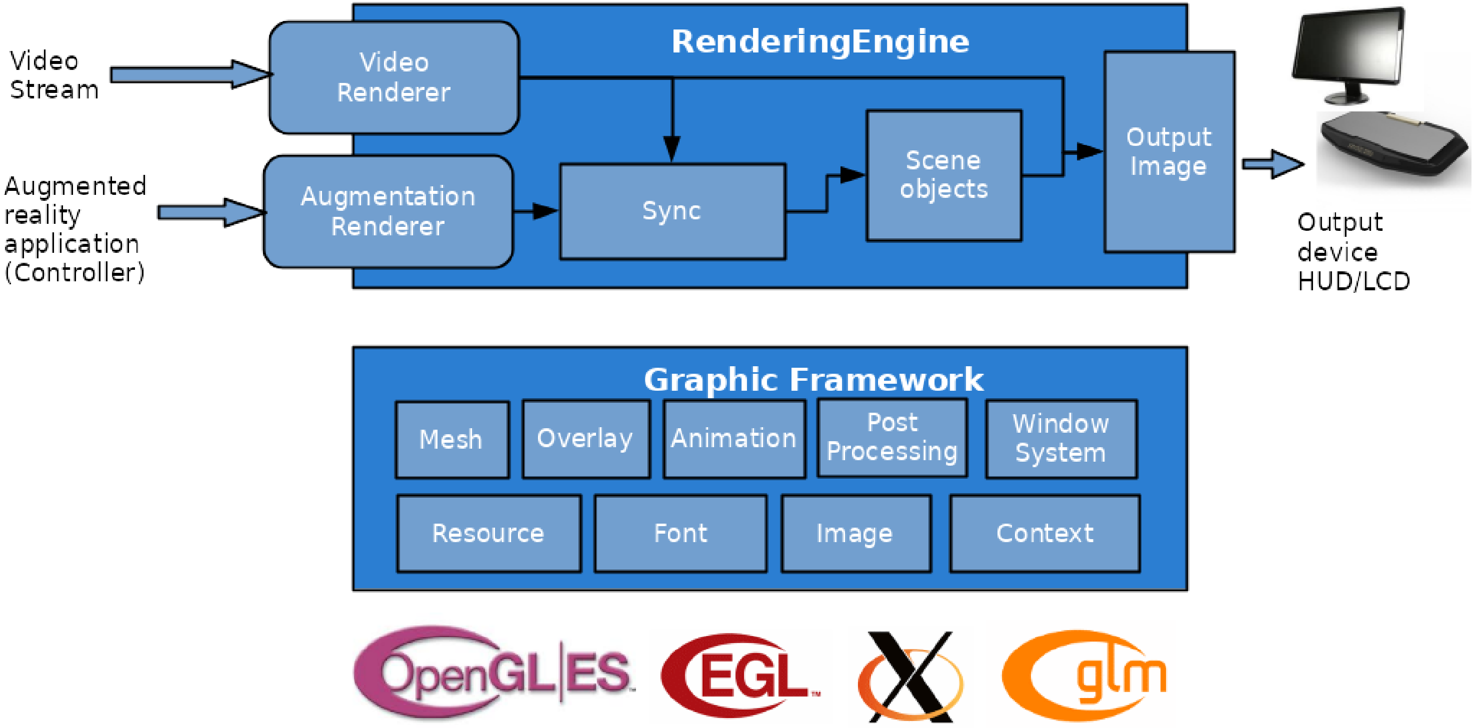
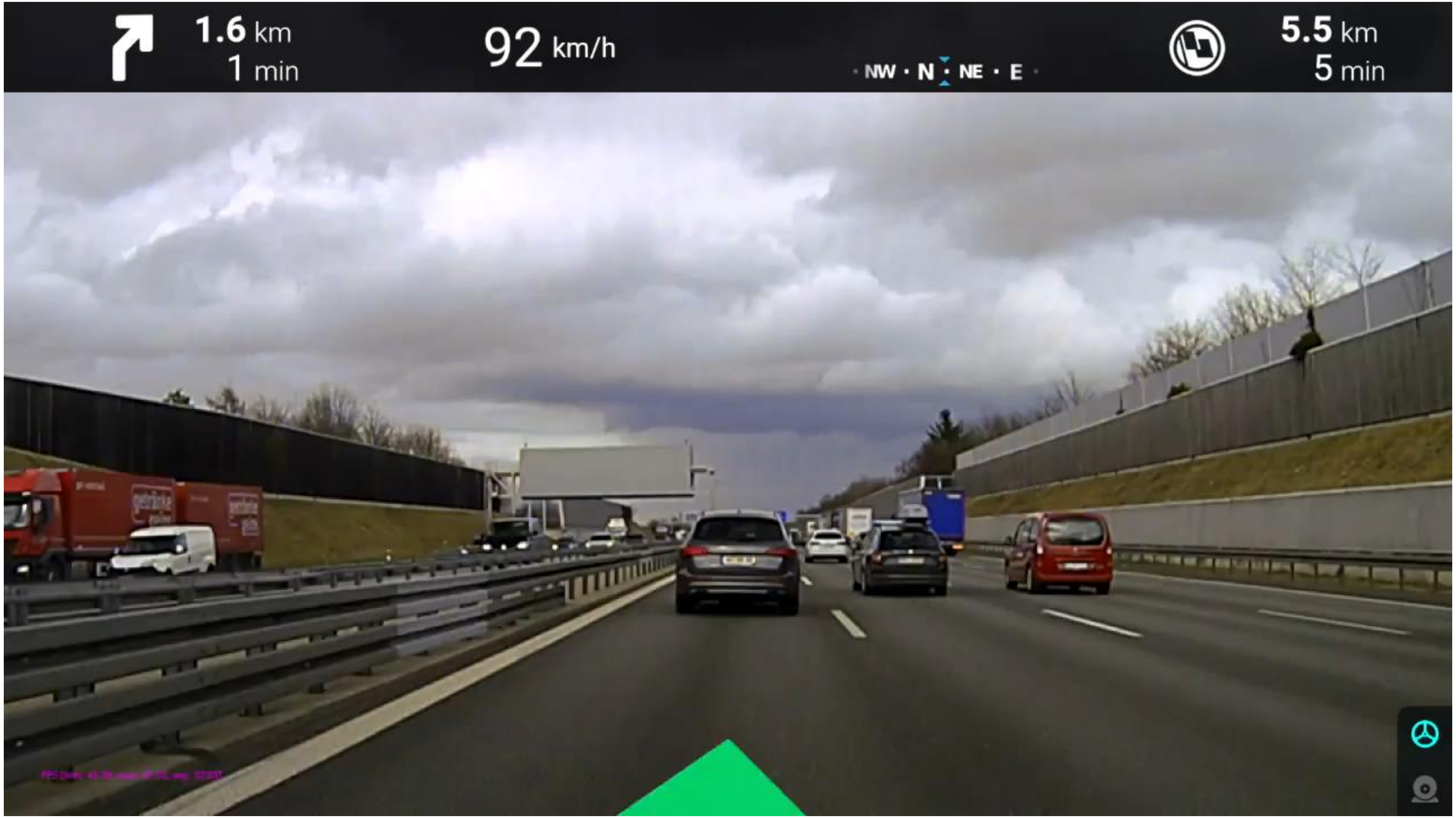


Figure – Rendering component

Augmented Guidance Demo Application



Summary: Key Technology Advantages

- Proved understanding of pragmatic intersection and synergy between fundamental theoretical results and final requirements
- Formal mathematical approaches are complemented by deep learning
- Solid GPU optimization
- Automotive grade solutions integrated with all the data sources in vehicle – data fusion approaches
- High robustness in various weather and road conditions, confidence is estimated for efficient fusion
- Closed loops designed and implemented to enhance speed and robustness of each component
- Integration with V2X and various navigation systems
- System architecture supports distributed HW setup and integration with existing in-vehicle components if required (environmental model, objects detection, navigation, positioner etc.)
- Hierarchical Algorithmic Framework design highly optimizes computations on embedded platforms
- Collaboration with scientific groups to integrate cutting edge approaches

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THANK YOU

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