



NVIDIA

ACCELERATING OPTICAL FLOW AND STEREO DISPARITY ESTIMATION USING THE NVIDIA A100 OFA ENGINE

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AGENDA

Optical Flow and Stereo Disparity Definition and Applications

What is Optical Flow? What is Stereo Disparity?

How are they used in computer vision applications?

OFA Engine - Motivation and Principles of Operation

Why did we build OFA? What can it do? How does it work?

Quality and Performance Metrics

How do we measure quality, and how does OFA do?

What throughput can OFA achieve?

Programming Flexibility

How can OFA be tailored to specific applications?





*OPTICAL FLOW AND
STEREO DISPARITY*
DEFINITION AND
APPLICATIONS



STEREO DISPARITY

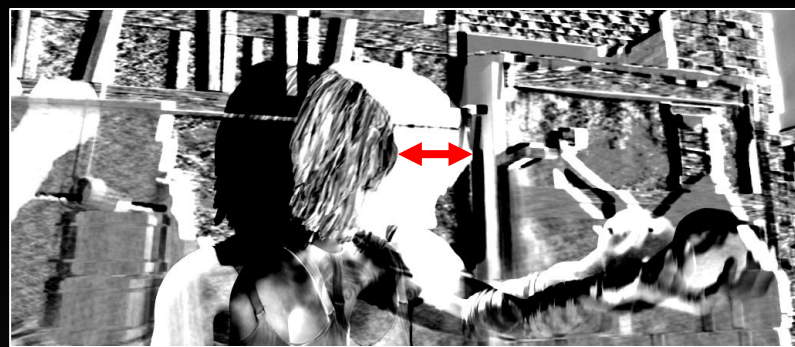
Depth from two parallel calibrated cameras



Left view



Right view



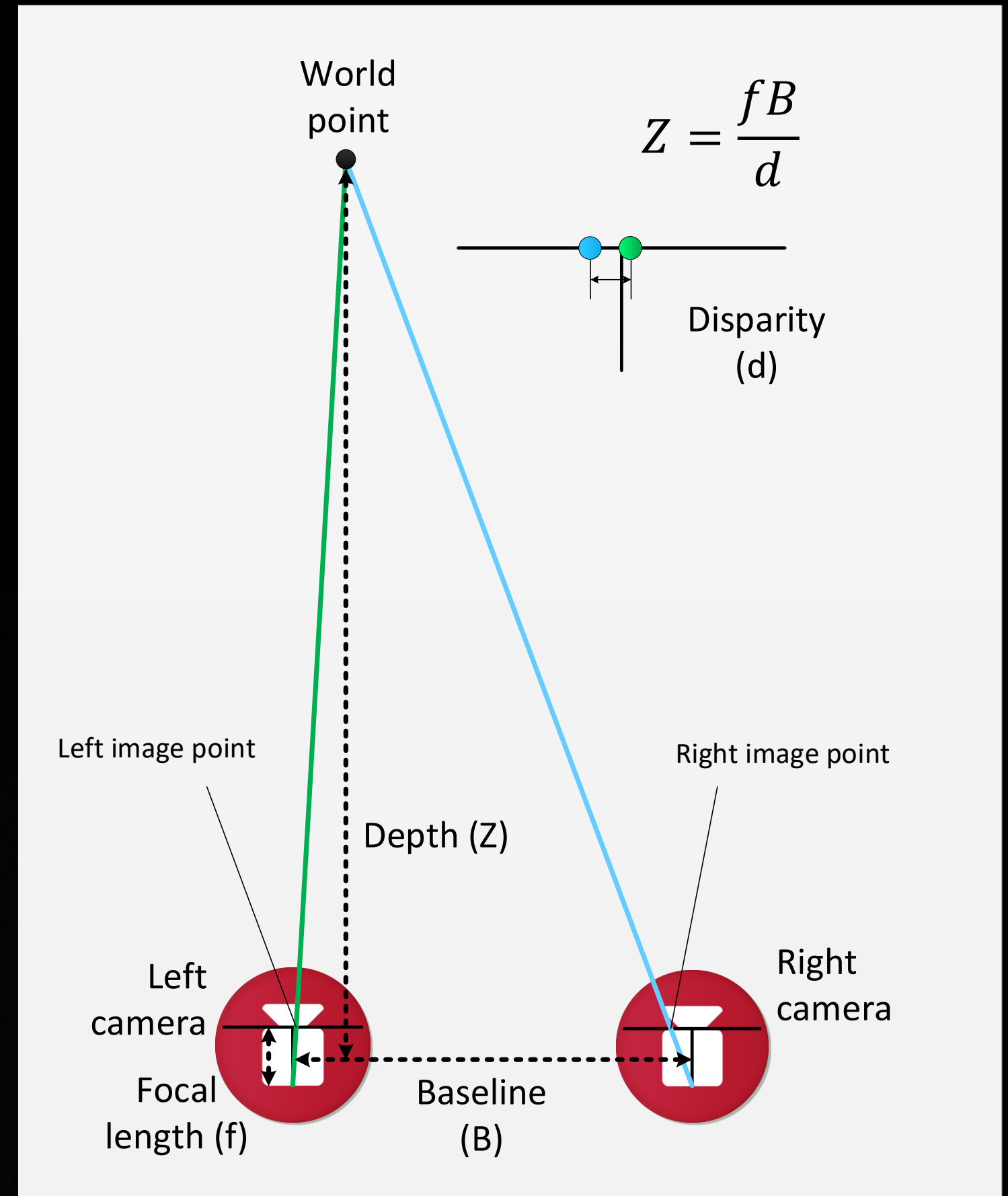
Disparity at one point



Dense disparity map

➤ Factors affecting stereo resolving power

- Baseline and focal length
- Camera field of view (30°, 60°, etc.) [lower is better]
- Sensor resolution [larger better] and pixel size [smaller better]



OPTICAL FLOW

Movement on image plane between two views from a single camera



Animated GIF



VIRTUAL REALITY

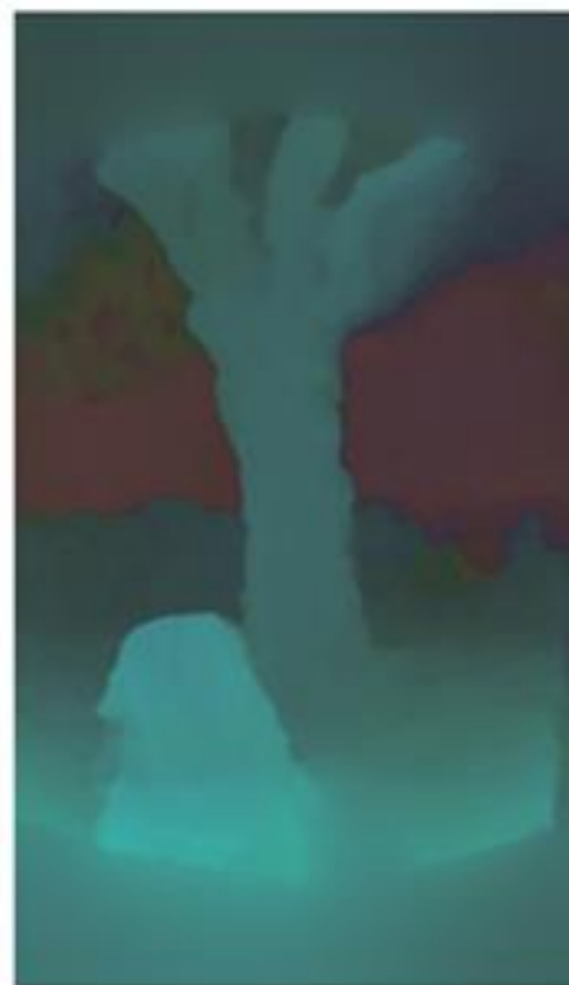
Facebook 3D-360 video project



Left Cropped Image



Right Cropped Image



Optical Flow Visualizations



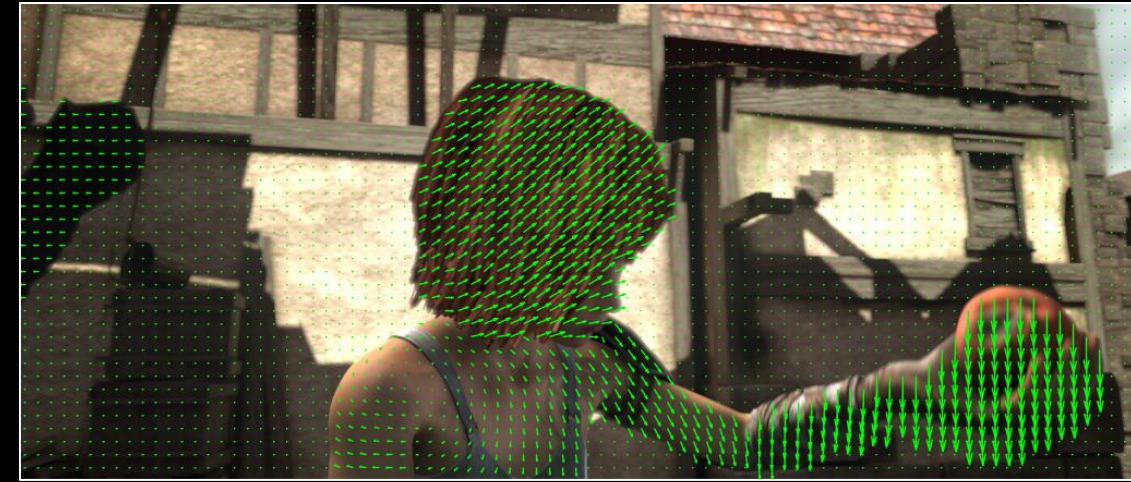
<https://www.facebook.com/Engineering/videos/10154013275372200/>

Code available: <https://github.com/facebook/Surround360>

IMPROVE GAMING EXPERIENCE

Frame rate upsampling

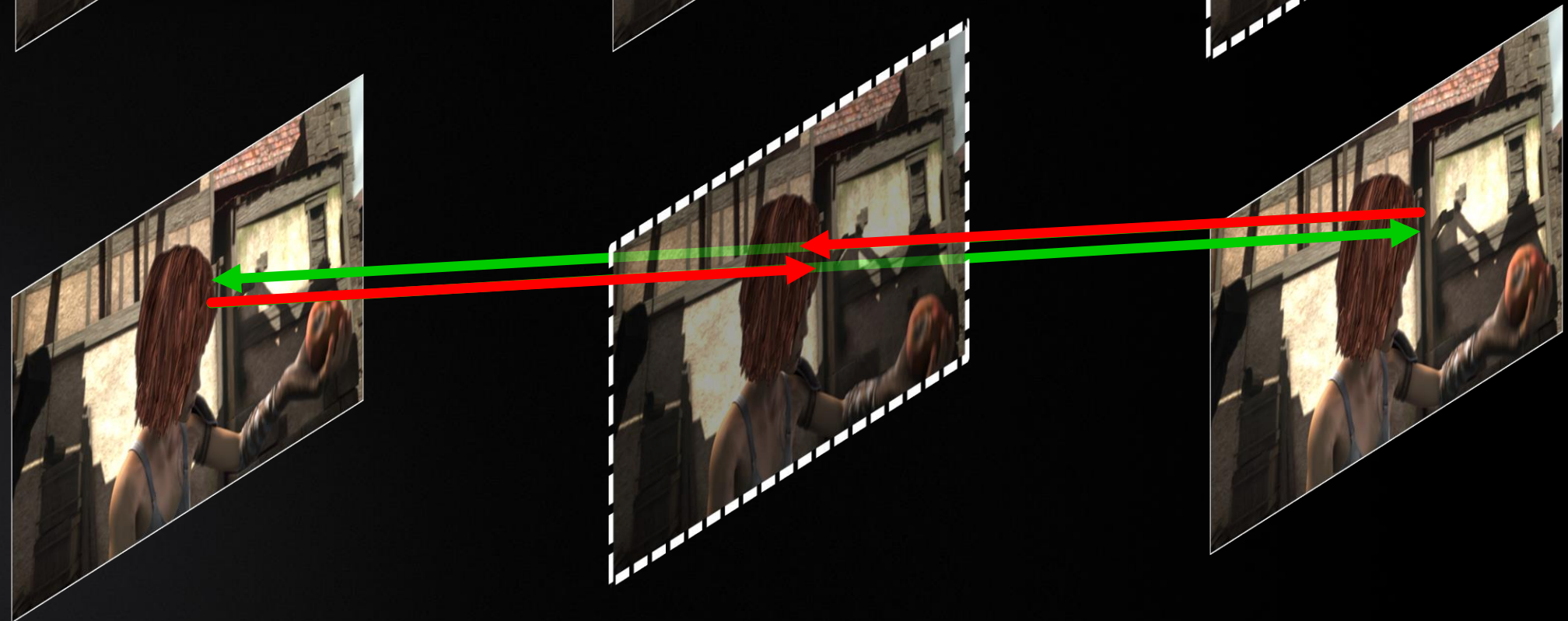
Interpolation vs Extrapolation



Oculus ASW uses flow-based extrapolation to maintain frame rate in hard-to-render scenes



Interpolation to increase frame rate is better when end-to-end delay is not as important



VIDEO UNDERSTANDING

OPTICAL FLOW IN VIDEO ACTION RECOGNITION

Two-stream CNN for Video Action Recognition

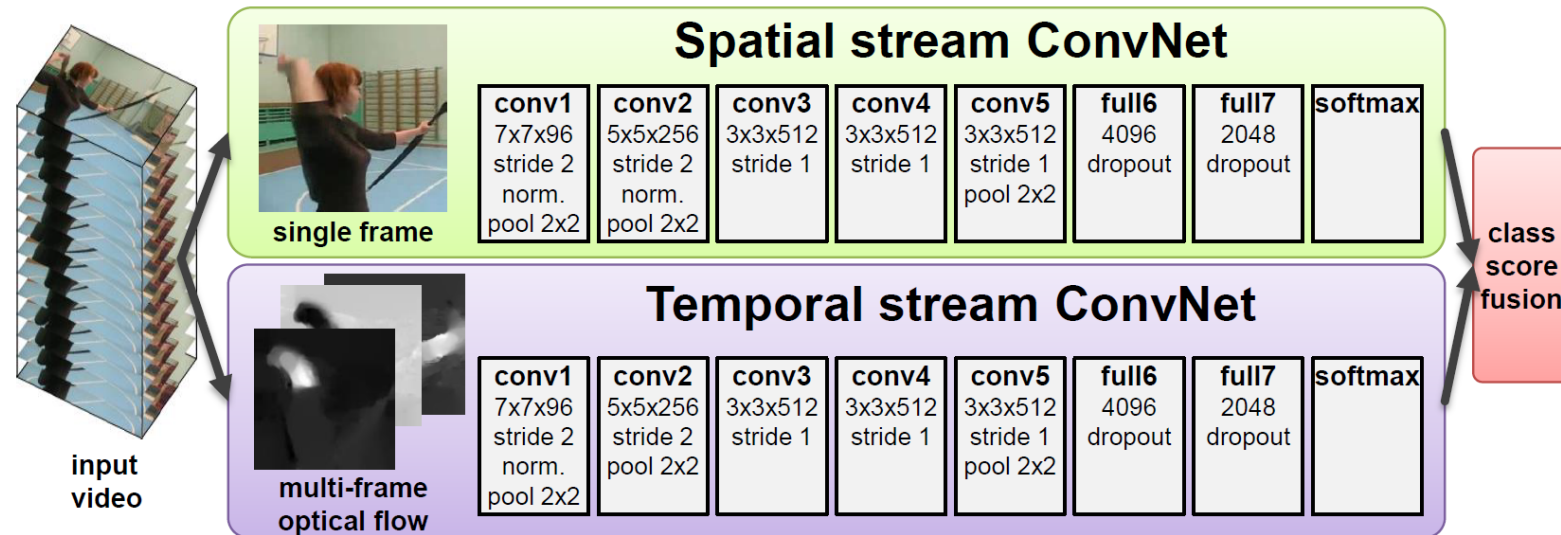


Figure 1: Two-stream architecture for video classification.

“Our experiments on two challenging datasets (UCF-101 and HMDB-51) show that the two recognition streams (image and optical flow) are complementary...”

Table 1: Individual ConvNets accuracy on UCF-101 (split 1).

(a) Spatial ConvNet.

Training setting	Dropout ratio	
	0.5	0.9
From scratch	42.5%	52.3%
Pre-trained + fine-tuning	70.8%	72.8%
Pre-trained + last layer	72.7%	59.9%

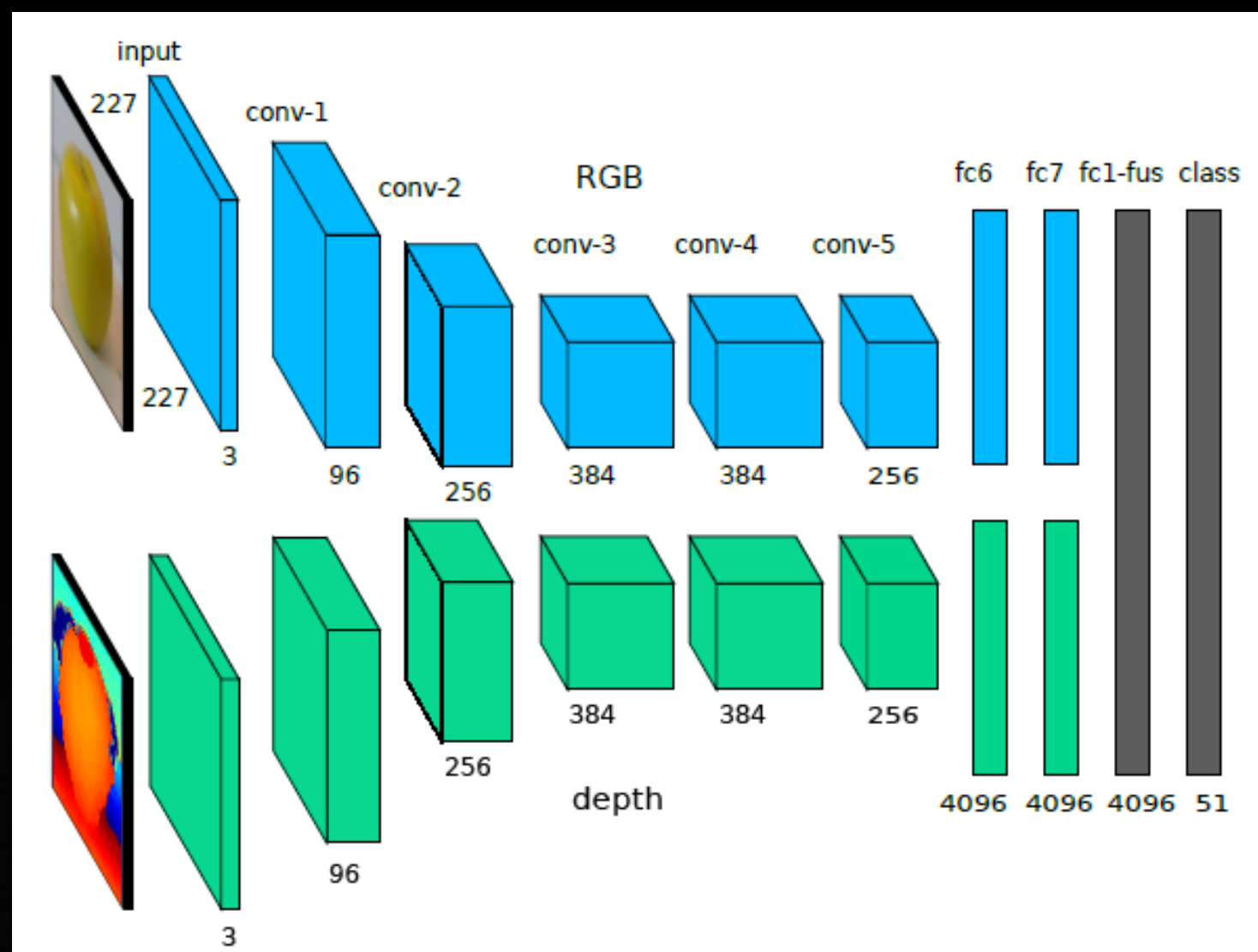
Table 3: Two-stream ConvNet accuracy on UCF-101 (split 1).

Spatial ConvNet	Temporal ConvNet	Fusion Method	Accuracy
Pre-trained + last layer	bi-directional	averaging	85.6%
Pre-trained + last layer	uni-directional	averaging	85.9%
Pre-trained + last layer	uni-directional, multi-task	averaging	86.2%
Pre-trained + last layer	uni-directional, multi-task	SVM	87.0%

From “Two-Stream Convolutional Networks for Action Recognition in Videos”, Simonyan and Zisserman, 2014

STEREO DISPARITY IN OBJECT RECOGNITION

Two-stream CNN for RGB-D object recognition



Recognition accuracy improvement

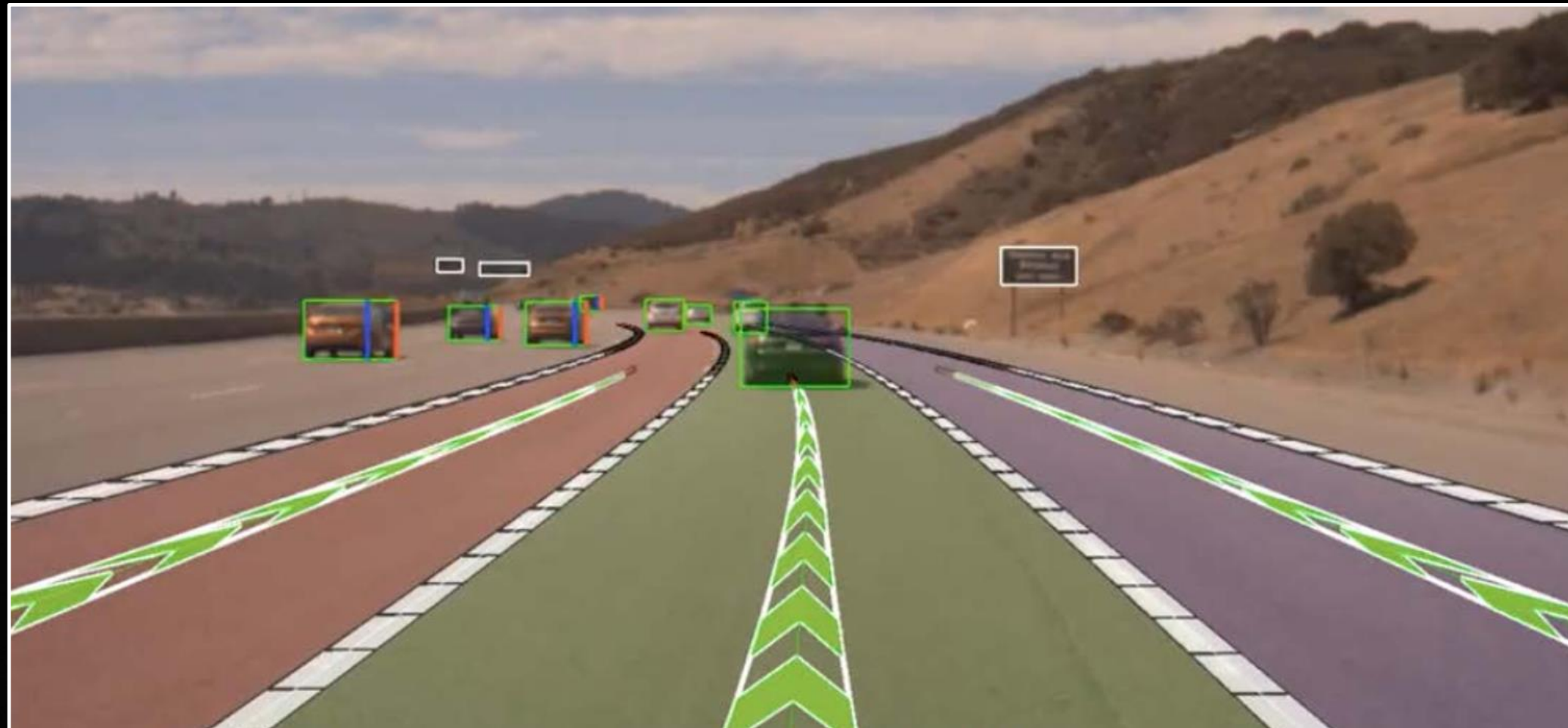
TABLE I: Comparisons of our fusion network with other approaches reported for the RGB-D dataset. Results are recognition accuracy in percent. Our multi-modal CNN outperforms all the previous approaches.

Method	RGB	Depth	RGB-D
Nonlinear SVM [15]	74.5 ± 3.1	64.7 ± 2.2	83.9 ± 3.5
HKDES [4]	76.1 ± 2.2	75.7 ± 2.6	84.1 ± 2.2
Kernel Desc. [14]	77.7 ± 1.9	78.8 ± 2.7	86.2 ± 2.1
CKM Desc. [3]	N/A	N/A	86.4 ± 2.3
CNN-RNN [22]	80.8 ± 4.2	78.9 ± 3.8	86.8 ± 3.3
Upgraded HMP [5]	82.4 ± 3.1	81.2 ± 2.3	87.5 ± 2.9
CaRFs [1]	N/A	N/A	88.1 ± 2.4
CNN Features [20]	83.1 ± 2.0	N/A	89.4 ± 1.3
Ours, Fus-CNN (HHA)	84.1 ± 2.7	83.0 ± 2.7	91.0 ± 1.9
Ours, Fus-CNN (jet)	84.1 ± 2.7	83.8 ± 2.7	91.3 ± 1.4

From “Multimodal Deep Learning for Robust RGB-D Object Recognition”, Eitel et al, 2015

AUTOMOTIVE USAGE

Driver Assistance and Autonomous Driving



ADAS task examples

Automatic emergency braking

Lane keep assistance

Hazard alert

Autonomous task examples

Free space / driving lane detection

Obstacle detection and identification

Mapping and localization

Path planning / driving policy

AUTOMOTIVE USAGE EXAMPLES

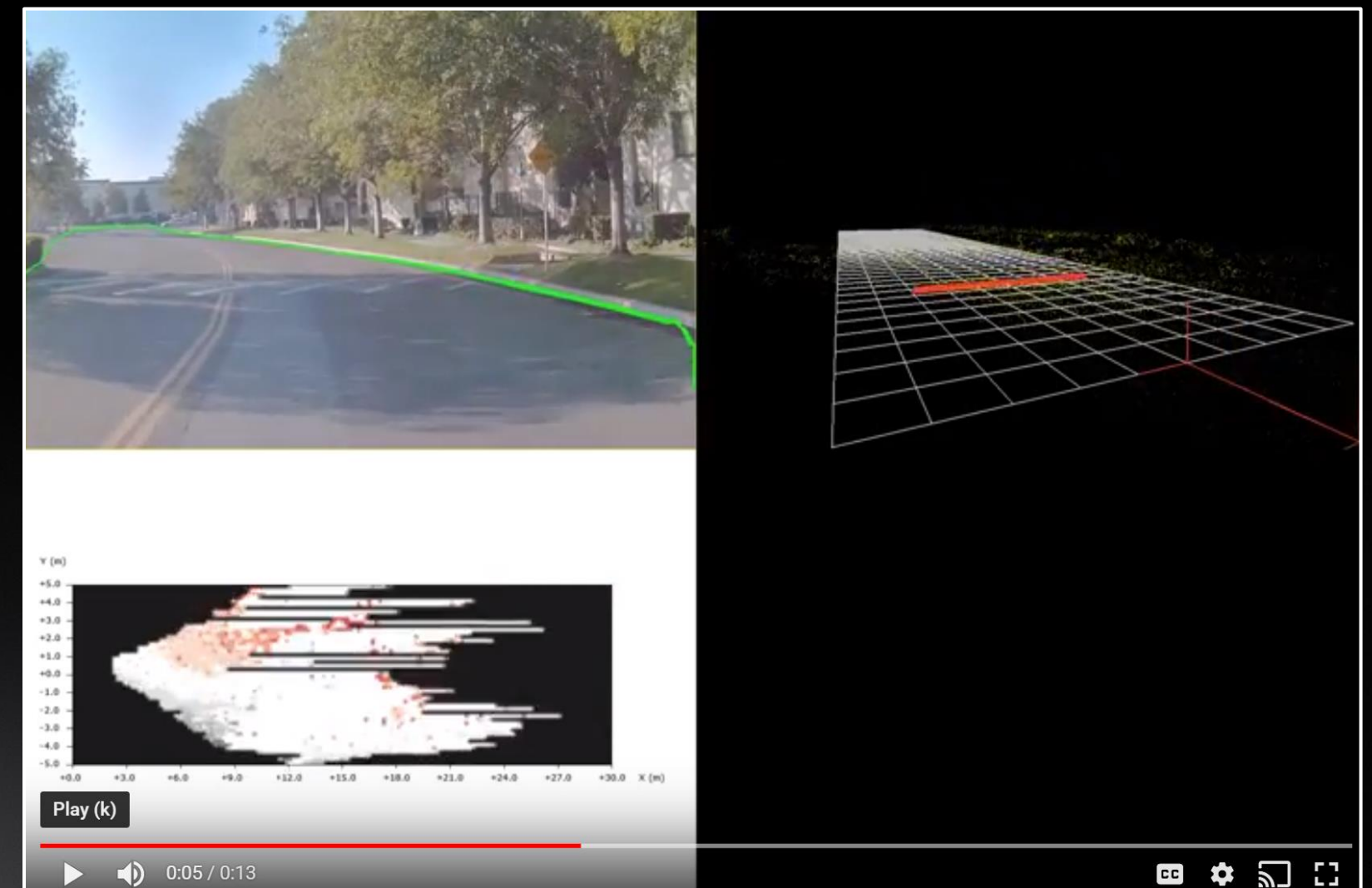
Road profile analysis

Potholes, bumps, hazardous objects, etc.

Hazardous object detection



Bump detection



ROBOTICS APPLICATIONS

Agricultural concept



Capture 3D scene with depth from stereo or structure-from-motion from mono camera

Analyze semantics using deep learning

Applications are many

Inspection

Targeted pest control

Trimming

Harvesting

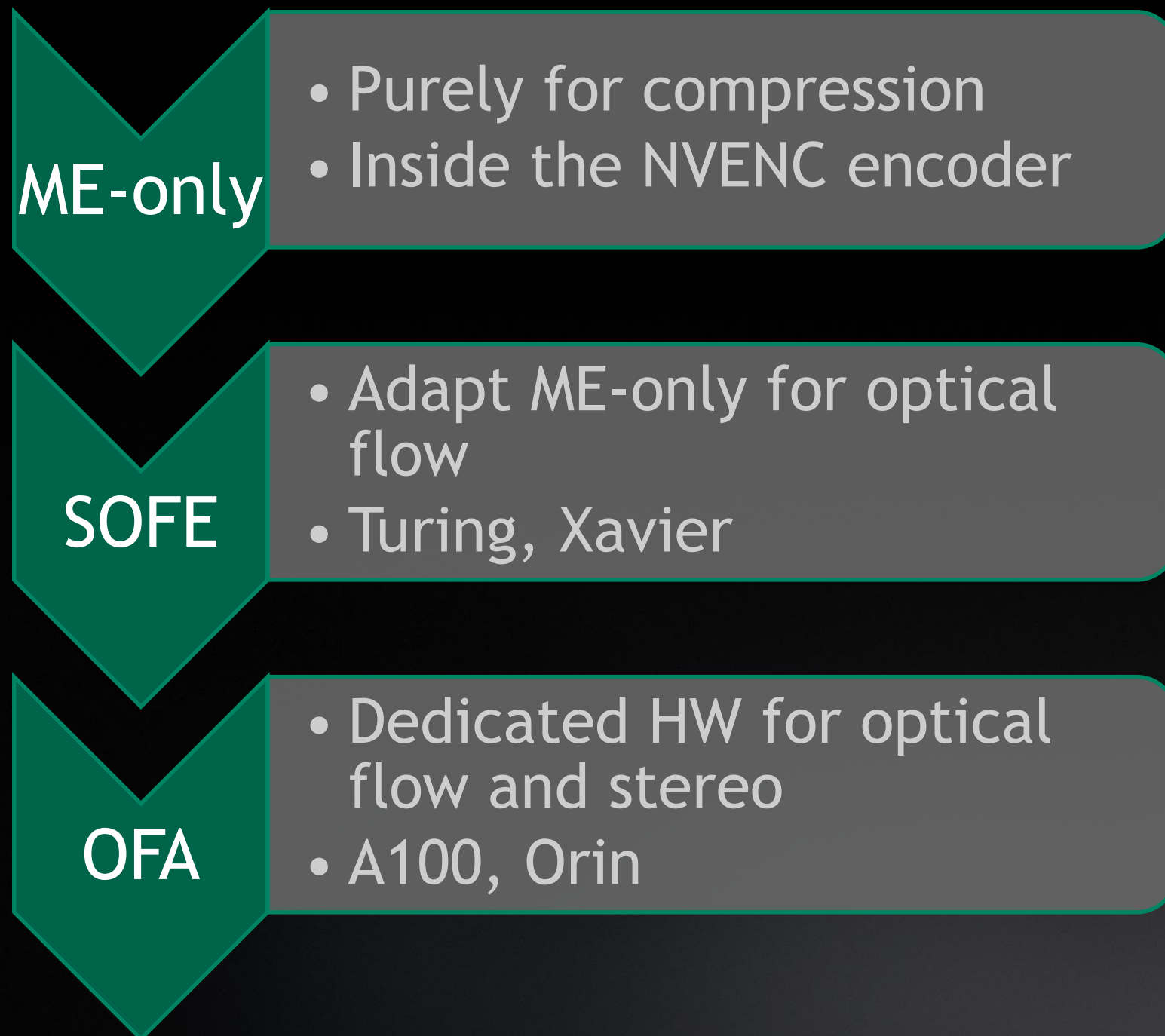


OFA ENGINE - MOTIVATION AND PRINCIPLES OF OPERATION



OFA = OPTICAL FLOW ACCELERATOR

Evolution of Nvidia Optical Flow / Stereo Hardware



MOTIVATION FOR OFA ENGINE

Quality:
Significant improvement over SOFE

Performance:
Match SOFE

Flexible application

Support:
Both Tegra and GPU

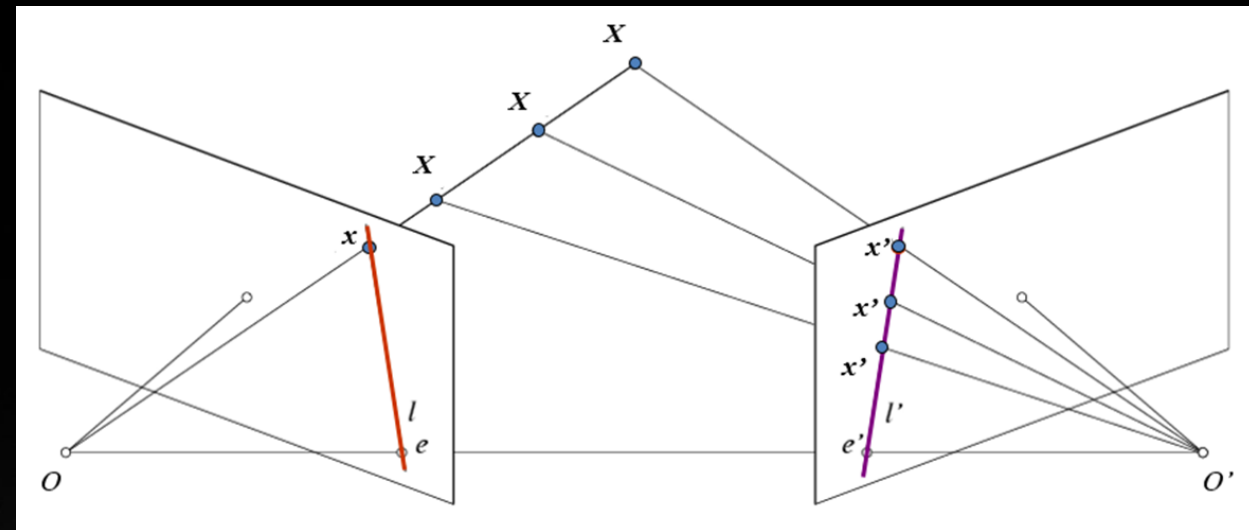


BASIS OF OFA ENGINE

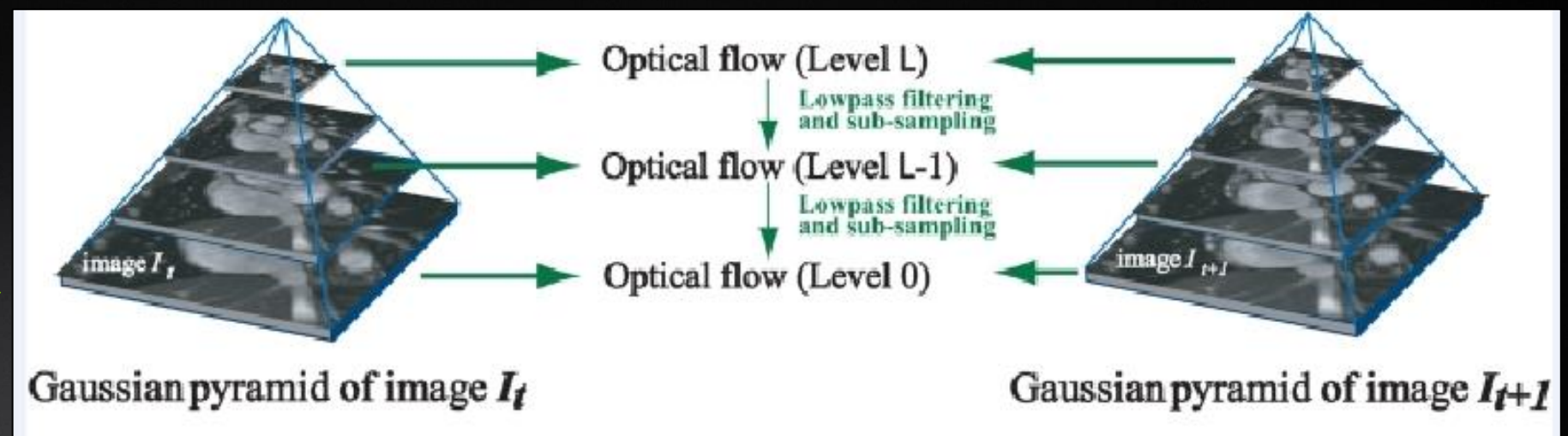
Real-time motion / depth smoothing (SGM)



Rigid static world & inter-camera geometry (Epipolar)



Optical flow w/o geometry and camera data (Pyramidal SGM)



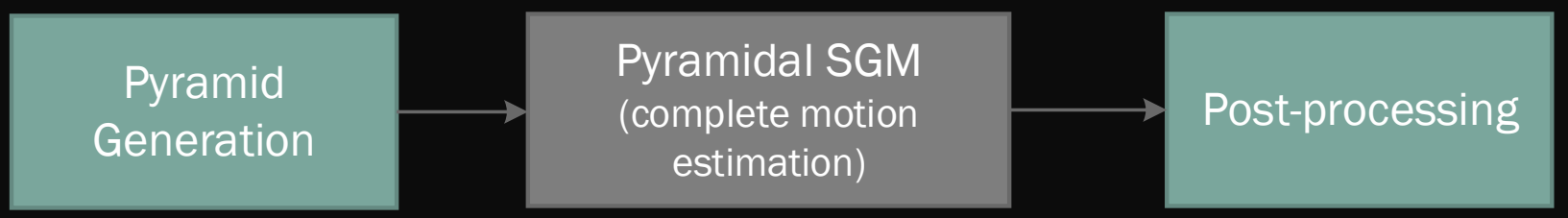
Legend

SW operation

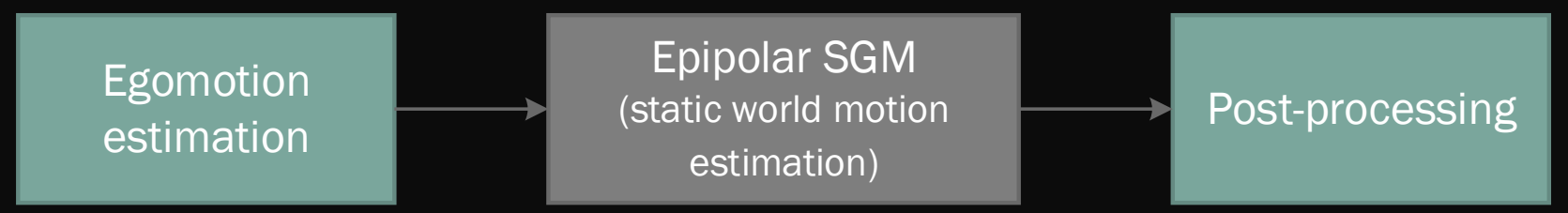
HW operation

MODES OF OPERATION

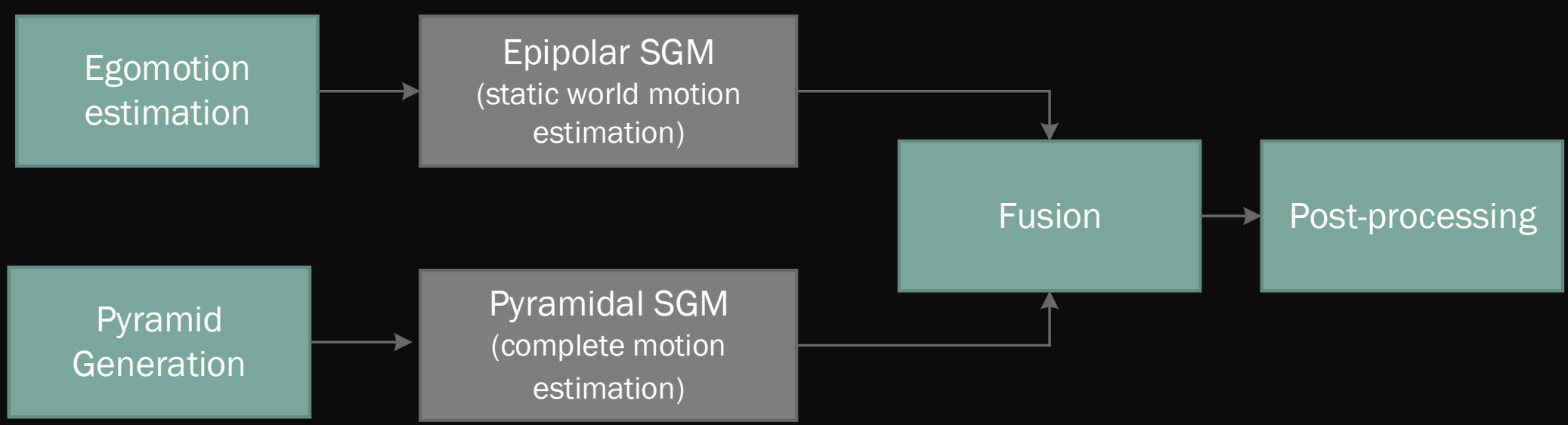
General optical flow



Static world optical flow



Fusion optical flow



Stereo



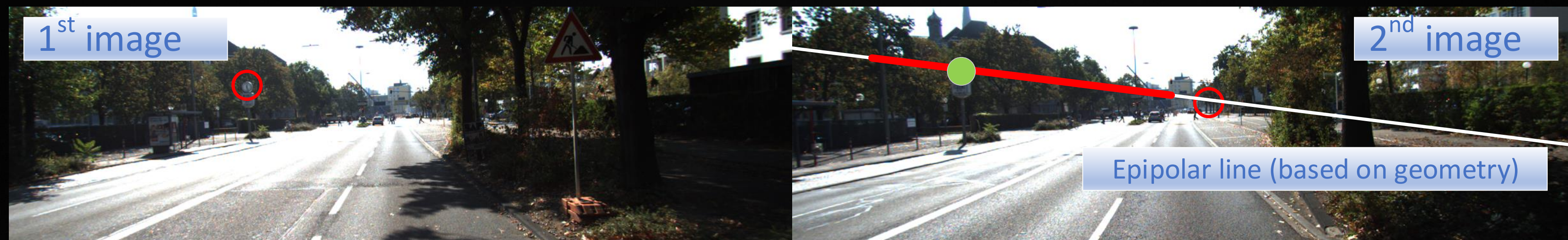
EPIPOLAR SGM FOR OPTICAL FLOW

Extending SGM to Optical Flow - Slide 1

Stereo case: matches appear along the same horizontal line

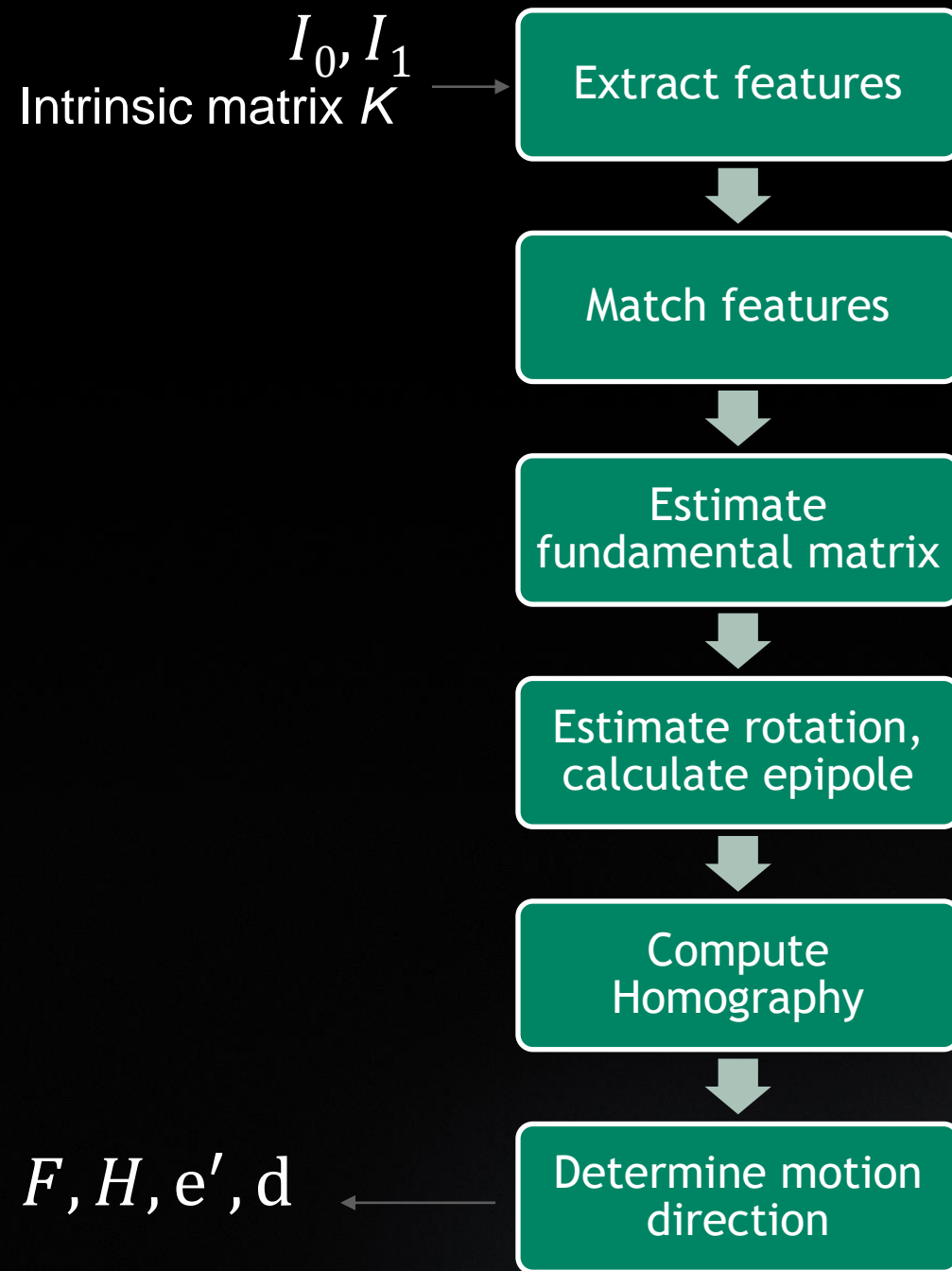


General two-camera case: matches appear along the epipolar line



EPIPOLAR GEOMETRY CALCULATION

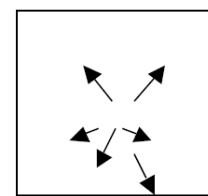
Extending SGM to Optical Flow - Slide 1



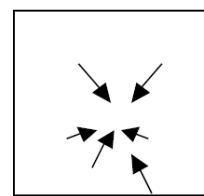
$$x'^T F x = 0$$

$$E = K' F K \rightarrow R \text{ \& \; epipole}$$

$$H = K R K'$$



$$T_z > 0$$



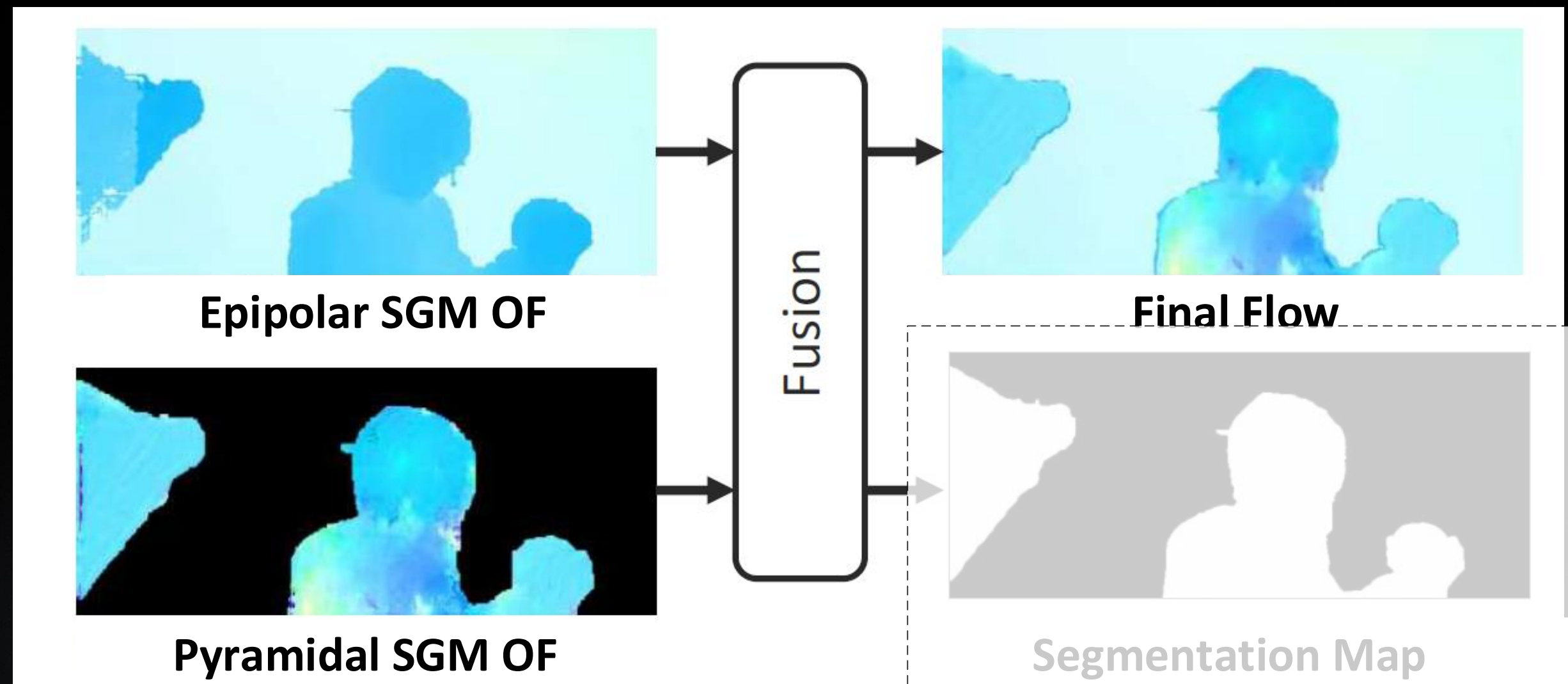
$$T_z < 0$$

- Relies upon knowledge of camera intrinsic parameters
- Tricky to do robustly

FUSION MODE

Step 1: Run OFA with epipolar & pyramidal SGM mode sequentially

Step 2: Fuse the two generated flow maps, using the corresponding cost maps or other data

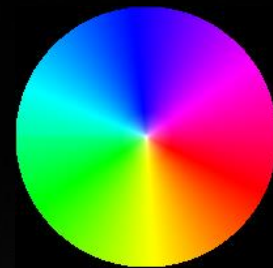
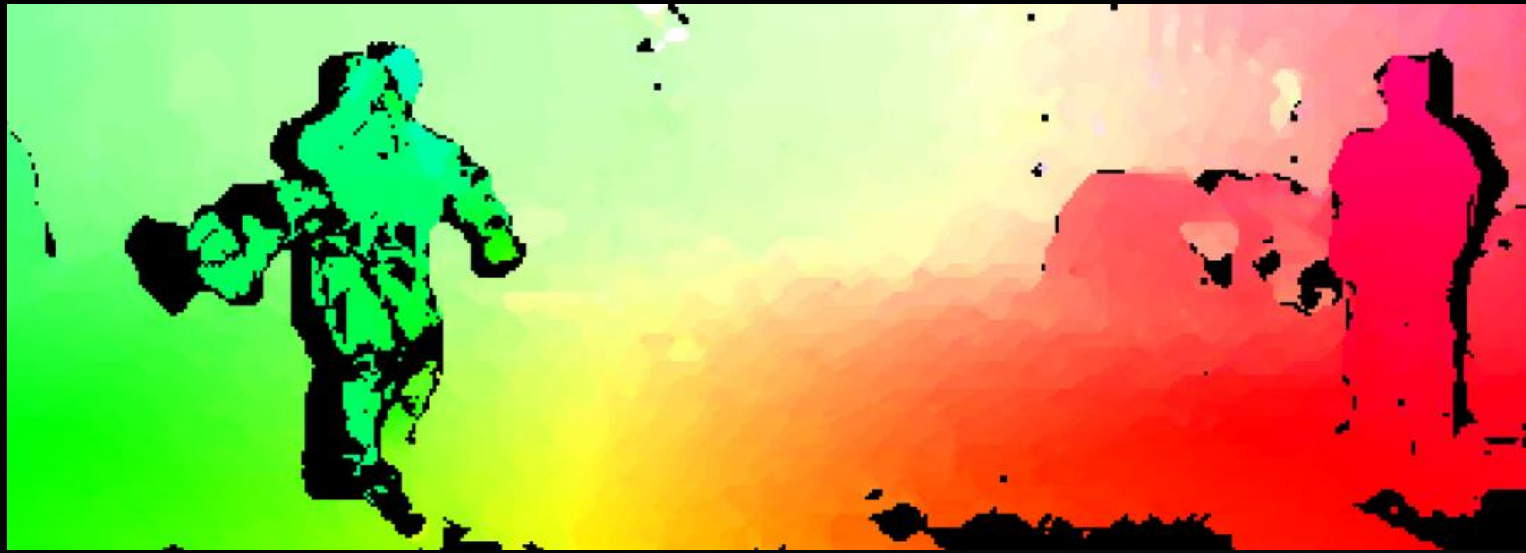




QUALITY AND PERFORMANCE

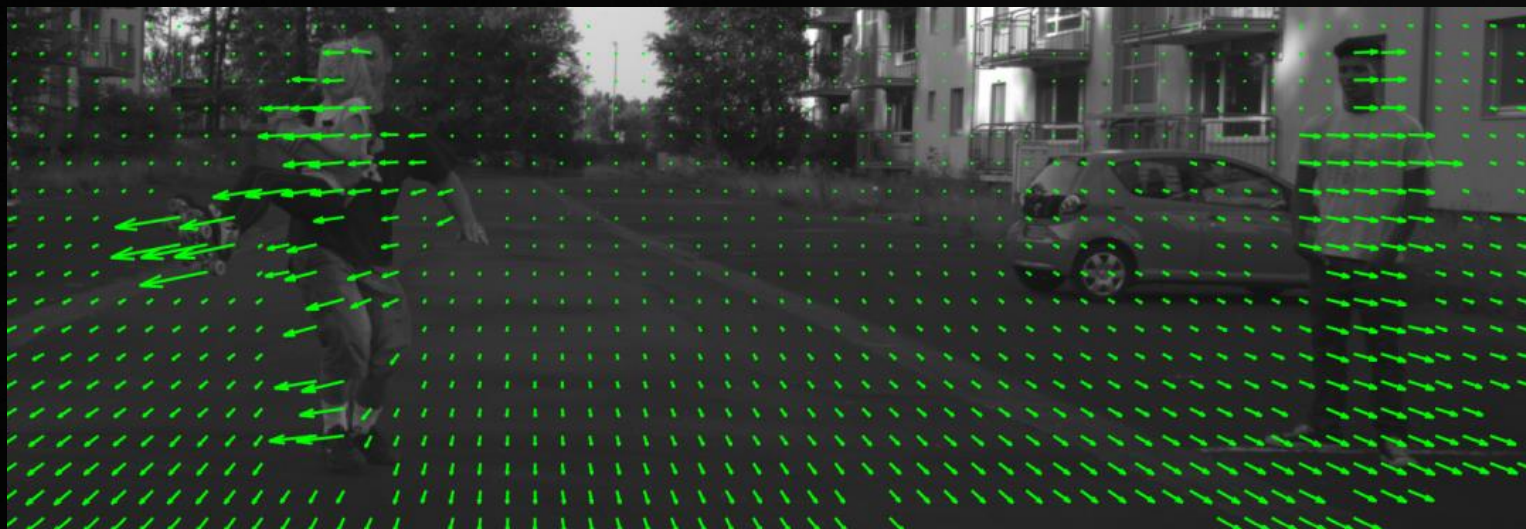


OPTICAL FLOW VISUALIZATION



▶ Color Map

- ▶ hue indicates direction of flow
- ▶ saturation indicates the flow magnitude
- ▶ Good for assessing smoothness and boundaries at full density

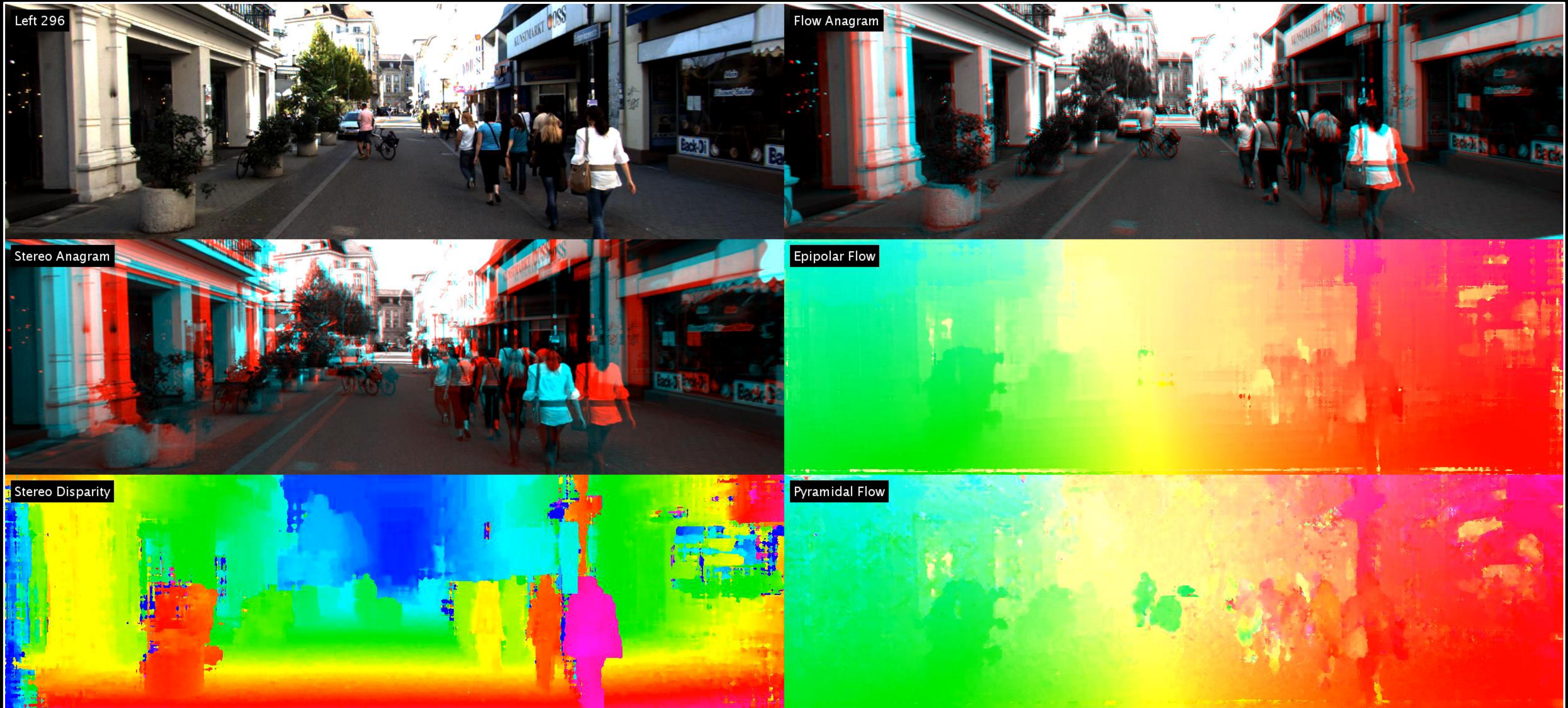


▶ Arrow map

- ▶ Each arrow represents the flow vector at that point
- ▶ Good for assessing accuracy, but at lower density

Example from MPI Sintel

EXAMPLE FROM URBAN DRIVING SCENARIO (COLORIZED)



EXAMPLE FROM KITTI 2015 BENCHMARK (ARROWS)

SOFE optical flow



OFA optical flow



The KITTI Vision
Benchmark Suite

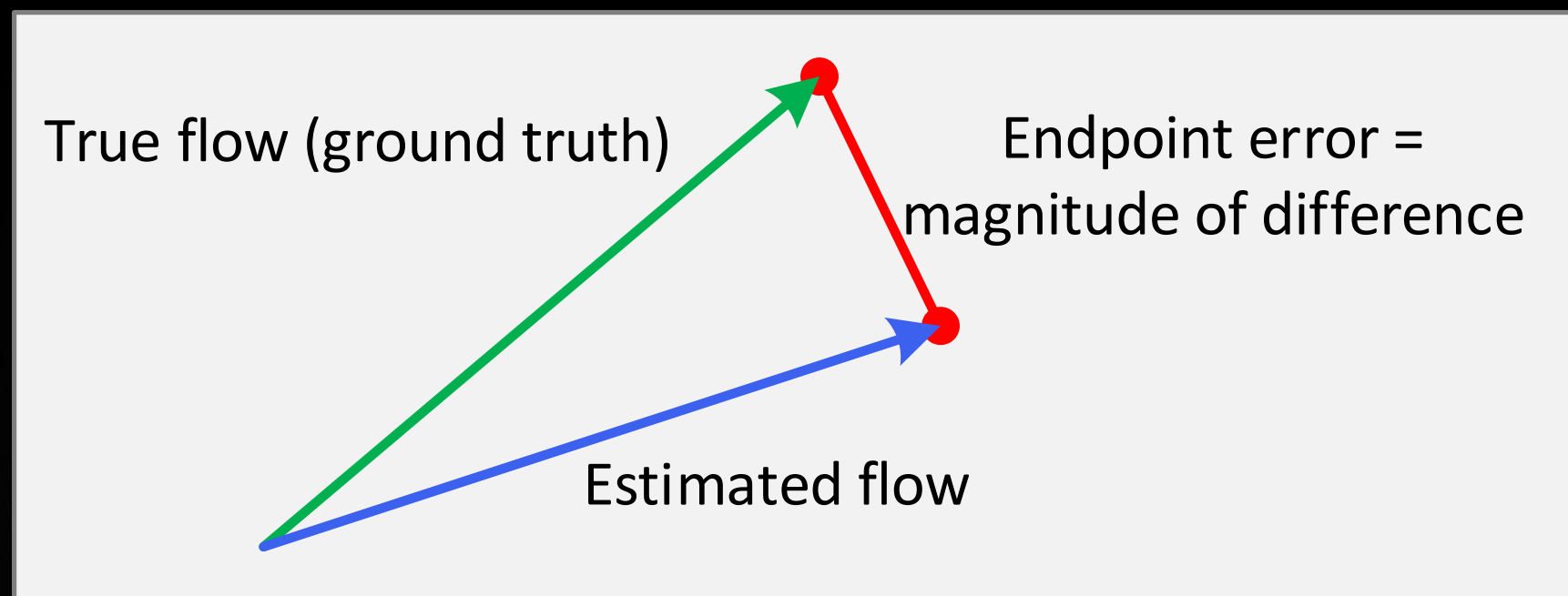
A project of Karlsruhe Institute of Technology
and Toyota Technological Institute at Chicago

home setup stereo flow sceneflow

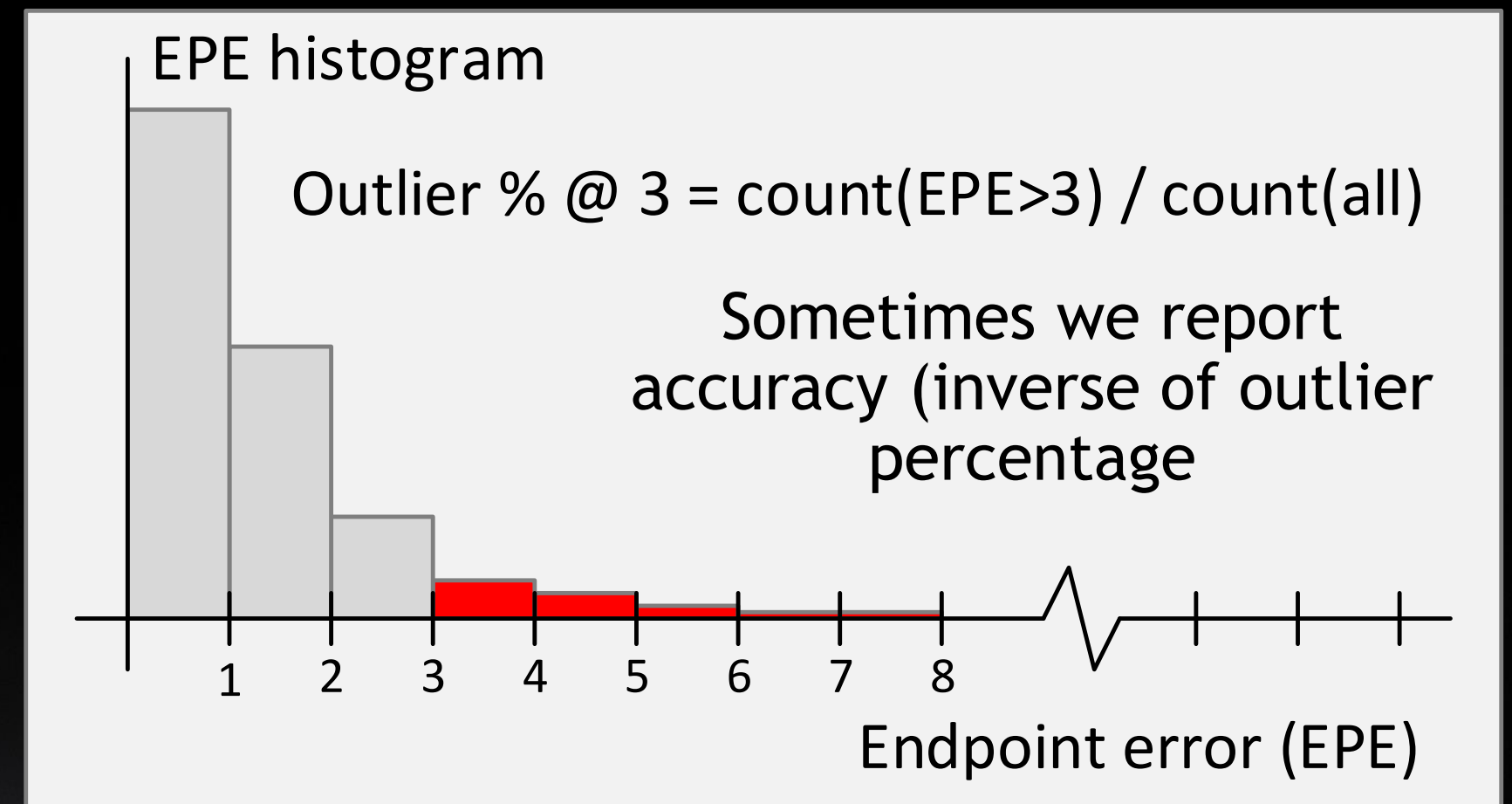


OPTICAL FLOW QUALITY METRIC DEFINITIONS

Endpoint error (EPE)



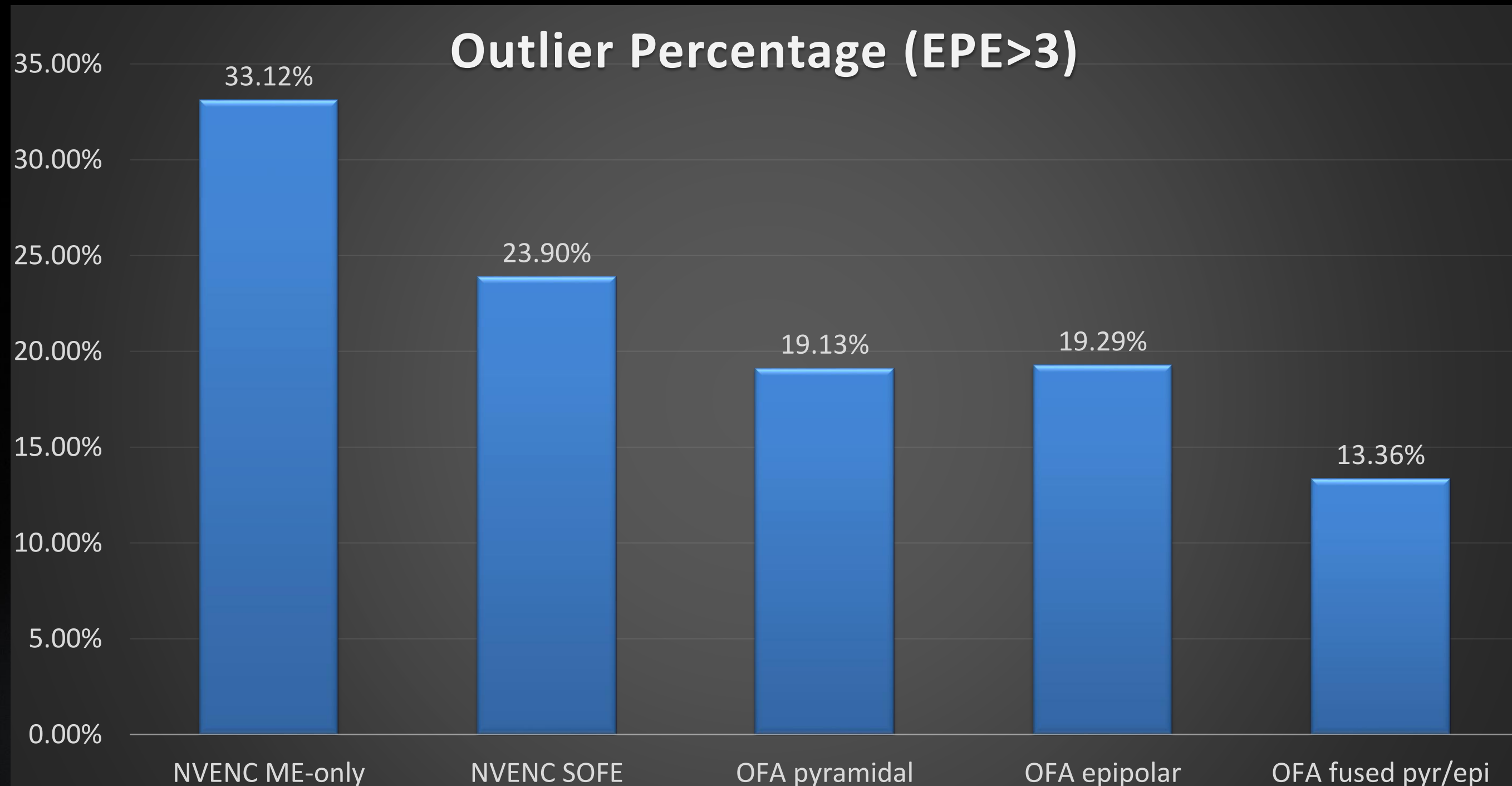
Outlier percentage



We use the same metrics for stereo disparity, although the arrows are always horizontal.

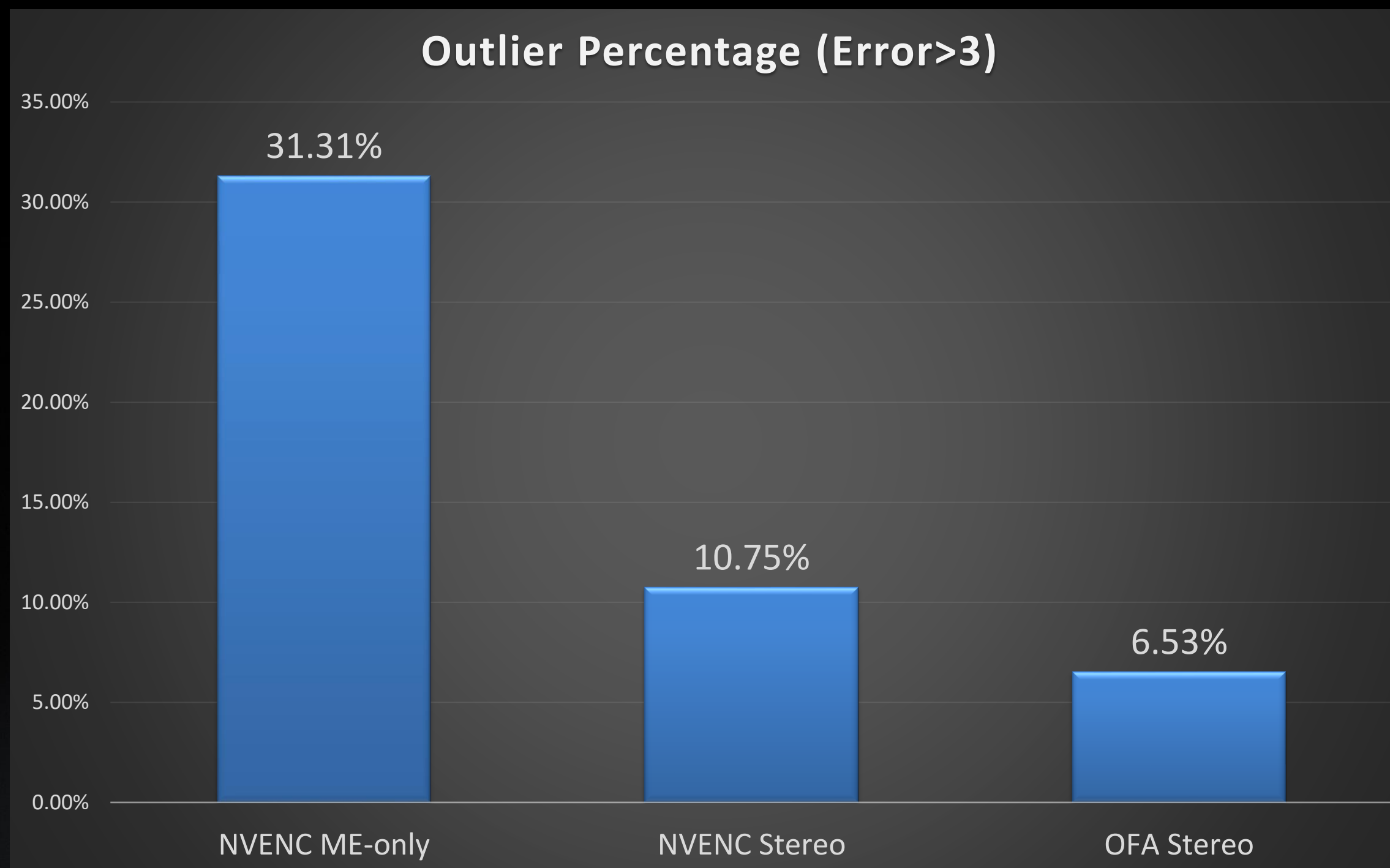
OPTICAL FLOW QUALITY SCORES - HW EVALUATION

KITTI 2015, Optical flow



STEREO QUALITY SCORES - HW EVALUATION

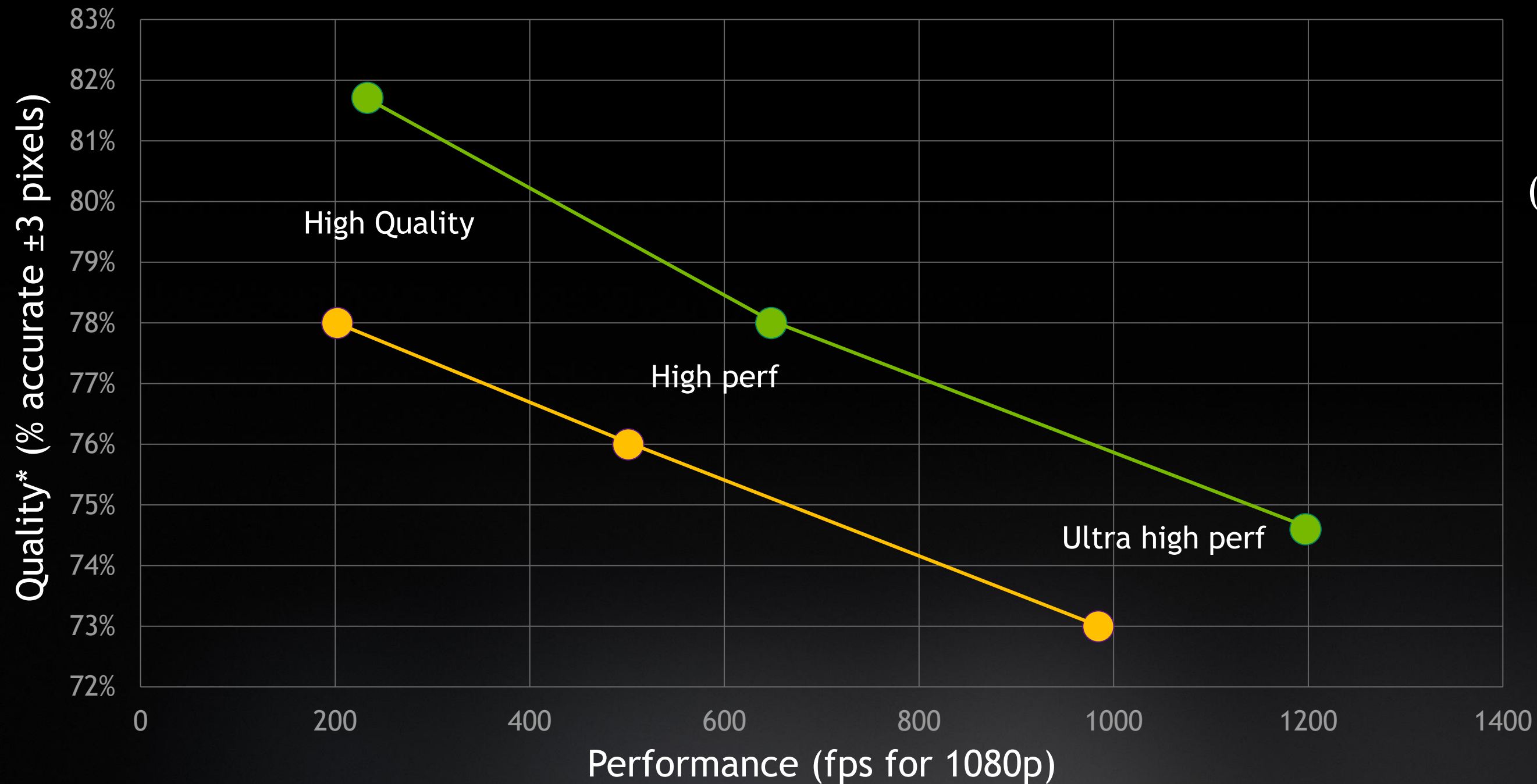
KITTI 2015 Stereo



OPTICAL FLOW SDK 2.0

Quality vs Performance

A100/Turing



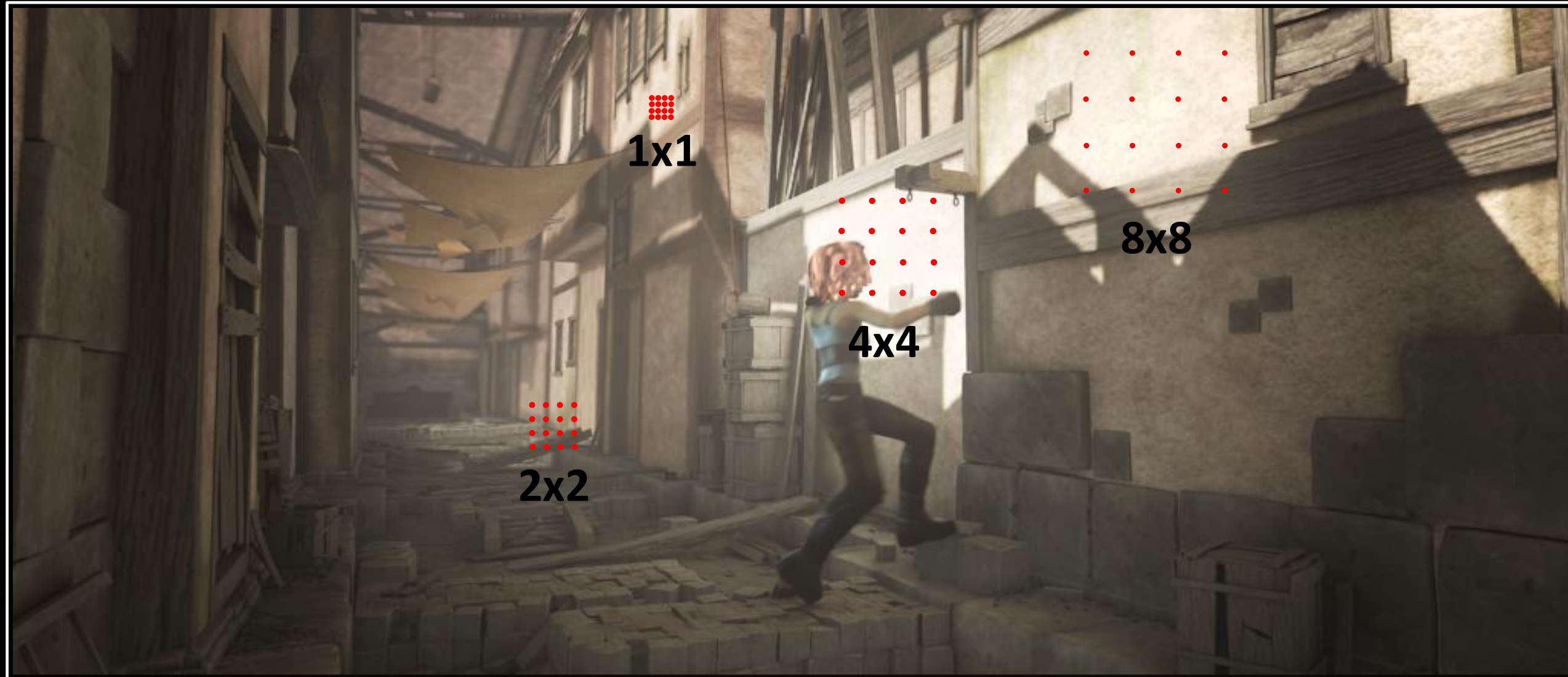
Accuracy vs. speed tradeoff achieved by tuning parameters
(inlier % at difference of 3 pixels)



PROGRAMMING FLEXIBILITY



OUTPUT DENSITY



Select density based on application

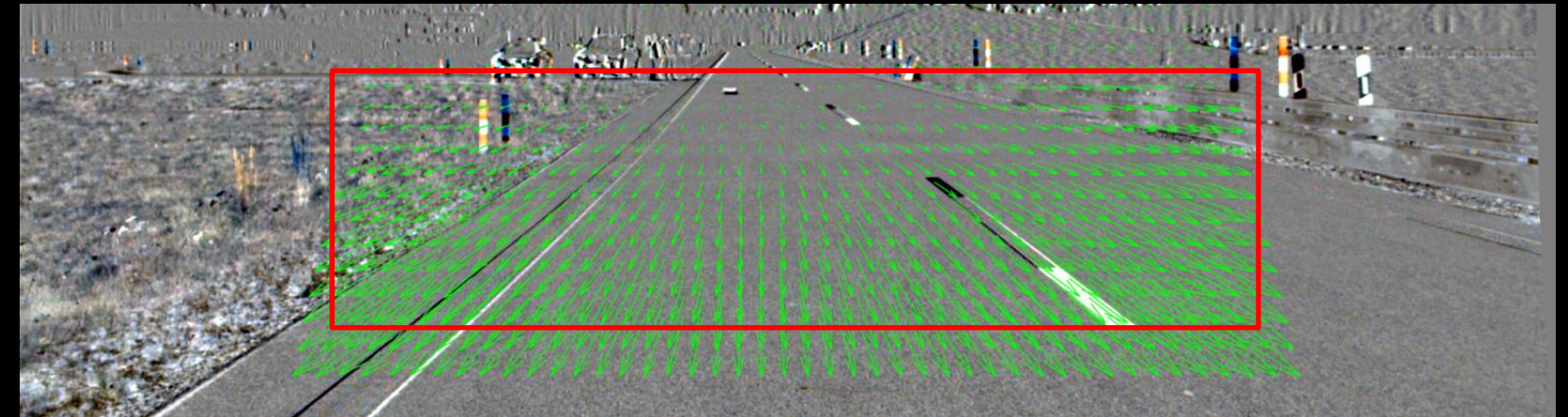
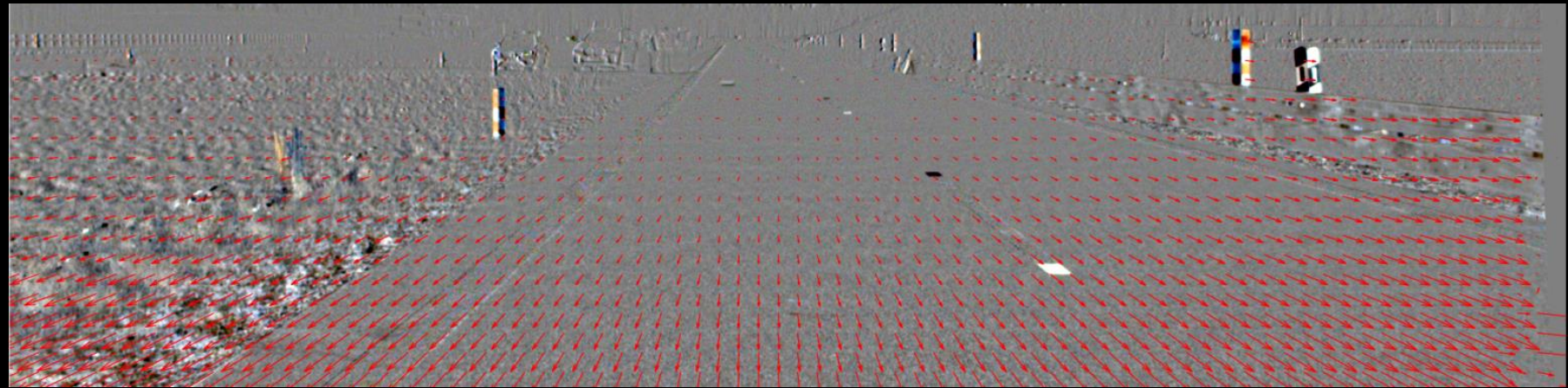


Trade off smaller details for speed



Use higher density with smaller ROIs

REGION OF INTEREST



Identify object or area of interest

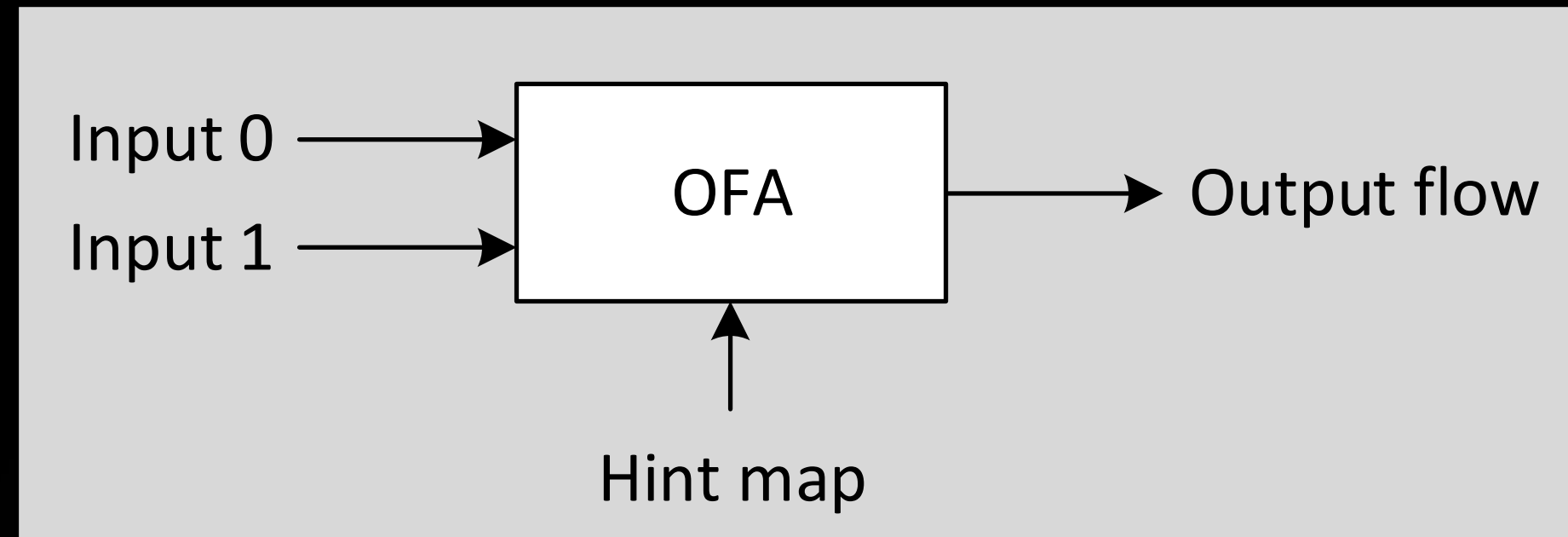


Define ROI with extended bounds $\pm N$ pixels
OFA only processes that area



Increase speed by focusing the engine

USING HINT MAPS



For stereo and pyramidal optical flow

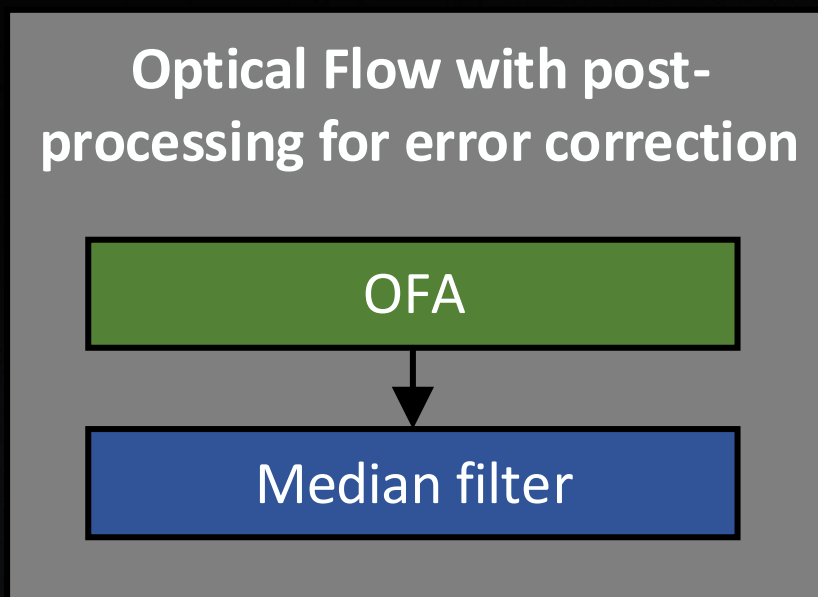
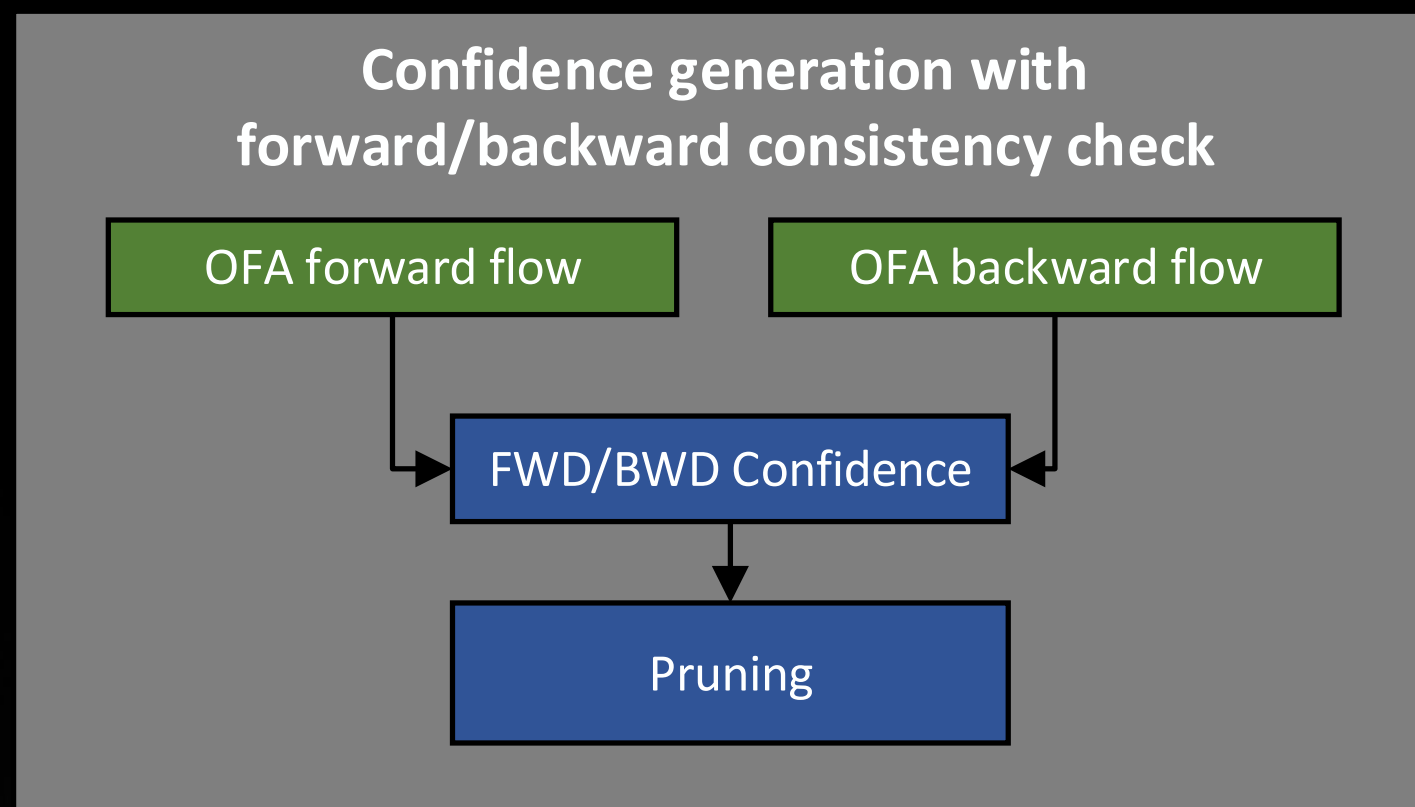


Hint map guides search area



Can come from any source

PROCESSING PIPELINES FOR CONFIDENCE MAPS AND POST-PROCESSING



Confidence maps are often required for downstream processing

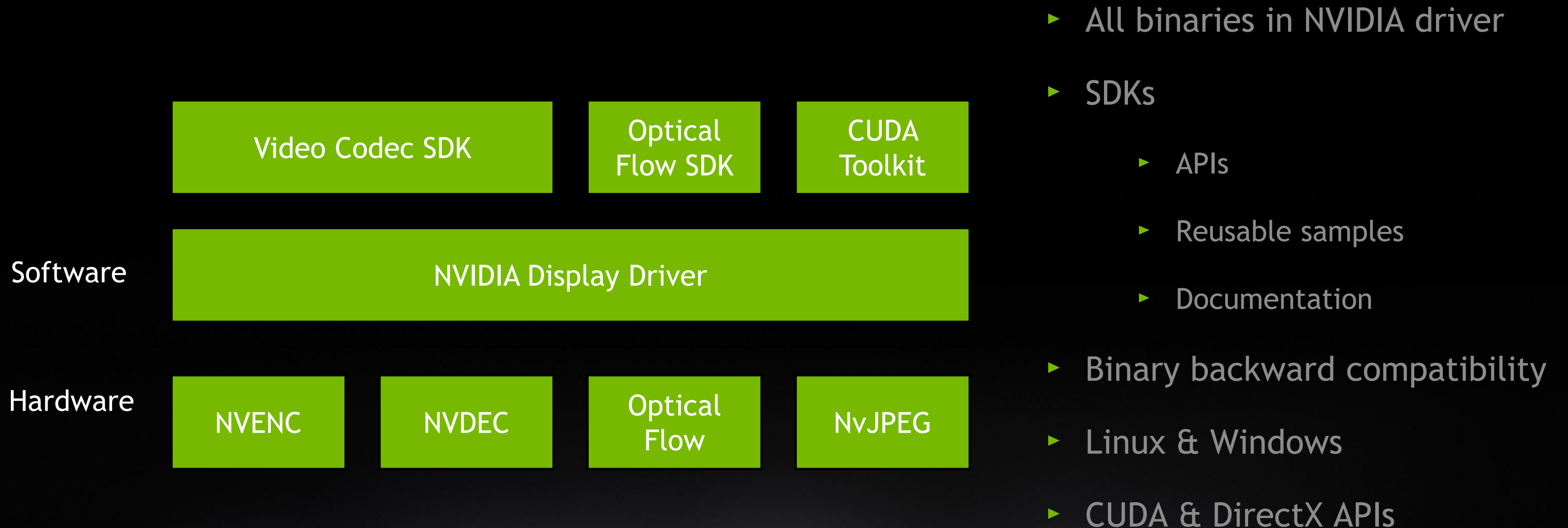


Post-processing can remove outliers

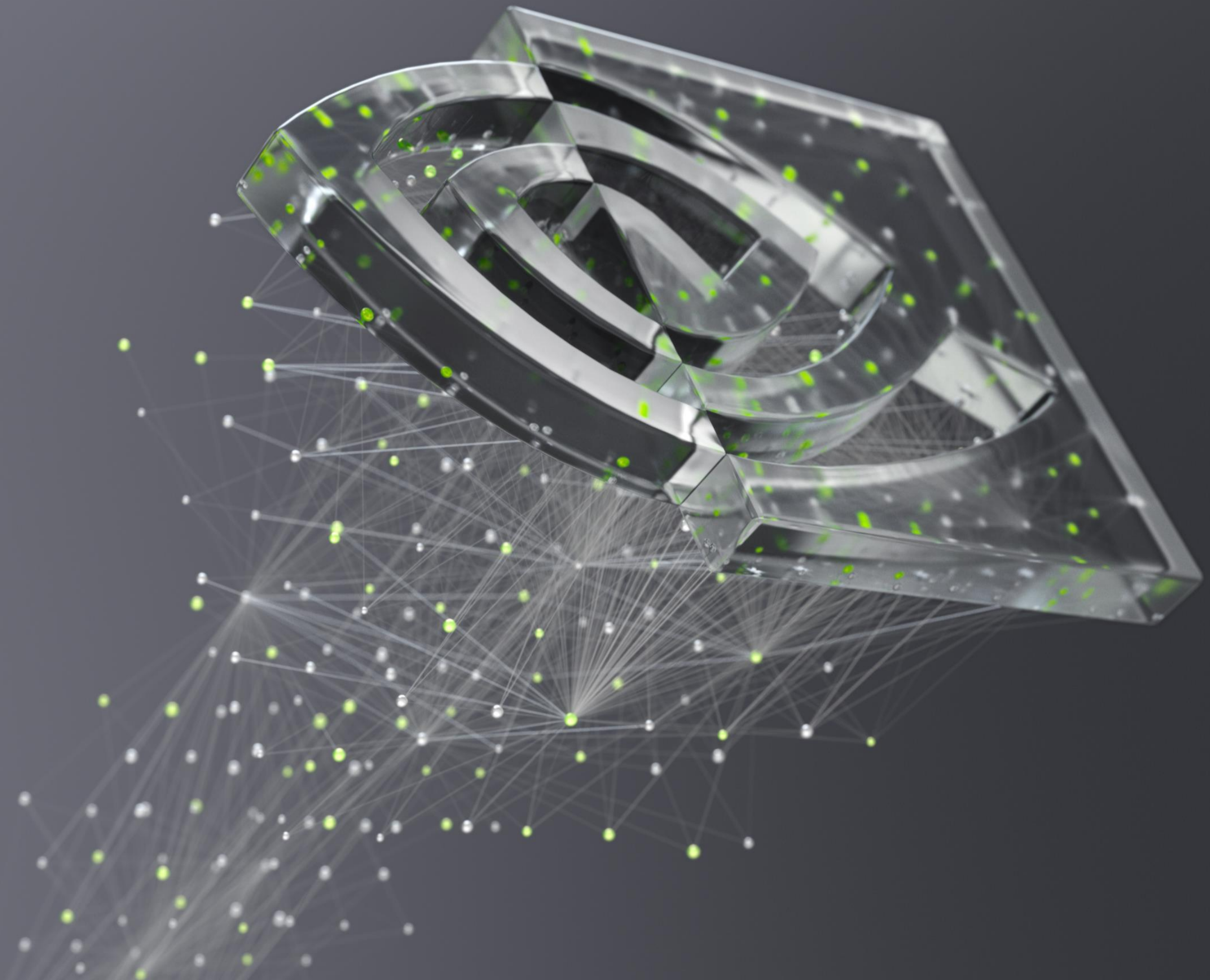


Done in SW, flexible

SOFTWARE



For more details, see: [S21337: NVIDIA Video Technologies: Video Codec and Optical Flow SDK](#)



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