Doing More with Less: Cost-Effective Infrastructure for Automotive Vision Capabilities





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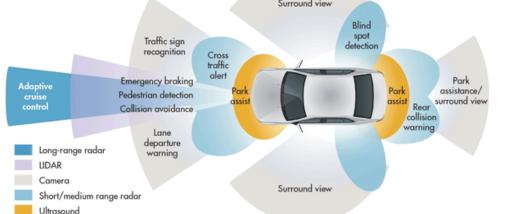
Motivation

Many safety-critical cyber-physical systems rely on advance capabilities to react to changing environmental conditions. cost-effective deployments of such capabilities have elusive. Such deployments will require software infrastrue enables multiple sensor-processing streams to be multiplex common hardware platform at reasonable cost, as well as methods for validating that required processing rates maintained.

Problem

Currently, advanced driver assistance system (ADAS) capabi have only been implemented in prototype vehicles using ha software, and engineering infrastructure that is very expense Prototype hardware commonly includes multiple high-end CPU and GPU chips and expensive LIDAR sensors. Focusing directly on judicious resource allocation, this project seeks to enable more economically viable implementations. Such implementations can reduce system cost by utilizing cameras in combination with low-cost embedded multicore CPU+GPU platforms.

	Supporting Real-Time Computer Vision Workloads								
ced sensing	Platform	Multiprocess Co-Scheduling							
hs. However, e remained ructure that lexed onto a as tools and tes can be bilities hardware,	 We are focusing on real-time systems where significant computing capacity must be provided with minimum monetary cost and size, weight, and power (SWaP). NVIDIA's Jetson TX2 fits these constraints. Image: the seconstraint of the	 Methodology: Run GPU-using programs in separate processes, record start and end times of thread blocks. Observations: GPU coscheduling can reduce 							
		 total time compared to sequential execution. Block times are minimally affected by coscheduling in this case. Coscheduled processes do 							
nsive. d CPU and	Memory Controller • 8GB OF DRAIVI. Memory Controller • An integrated GPU.	not truly share the GPU, but							

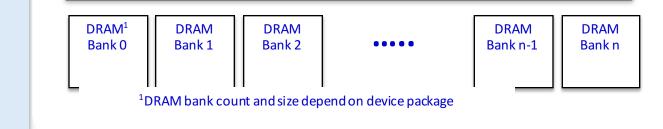


http://roboticsandautomationnews.com/wp-content/uploads/2016/09/adas-illustration.gif

Objectives

This project focuses on three principal objectives:

- New implementation methods for multiplexing disparate image-processing streams on embedded multicore platforms augmented with GPUs.
- New analysis methods for certifying required streamprocessing rates.
- New computer-vision methods for constructing imageprocessing pipelines.



The DRAM is shared between the host CPU and GPU.

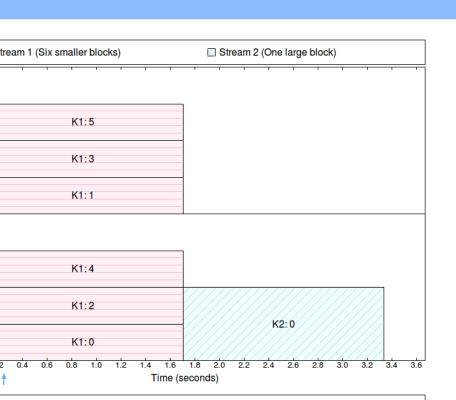
Inferring GPU Scheduling Behavior

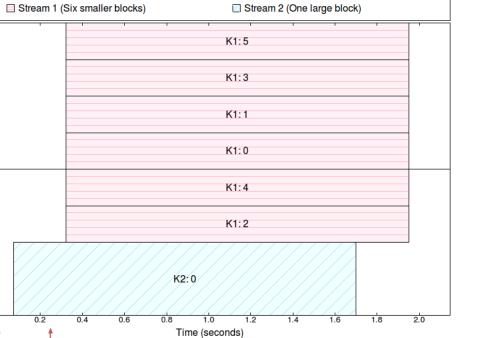
Motivation:

- Scheduling of GPU programs can result in wasted capacity. Methodology:
- Designed an experimentation framework to infer GPU scheduling behavior.
- Developed rules to describe scheduling behavior seen in experiments.

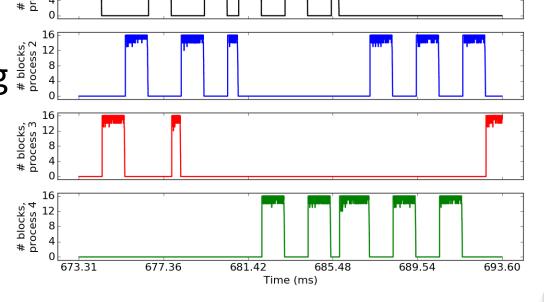
Future work:

• Write middleware to reorder GPU work.



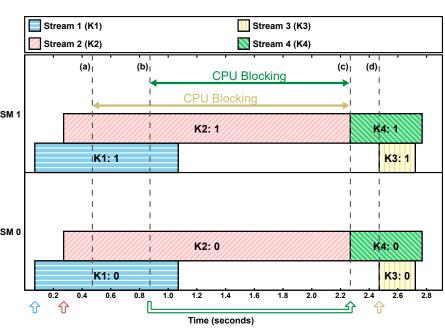


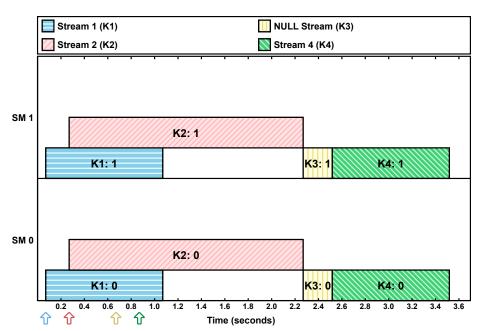
are multiprogrammed. Our observations imply that using ^{*} multiple threads within a single process have more potential to improve utilization.



Implicit Synchronization

- GPU synchronization blocks GPU operations, resulting in capacity loss.
- The CUDA API can cause unexpected implicit synchronization.
- Future middleware may reduce blocking by re-scheduling some implicit-sync API calls.





Case Study: Pedestrian-Detection Tasks

Choice of Software: Histogram of oriented gradients (HOG) **Methodology**: We transformed HOG in OpenCV into a DAG. We compared the response times of successively finer-grained notions of DAG scheduling, corresponding to monolithic, coarse-grained, and fine-grained HOG DAGs, while supporting six cameras. **Observations**:

Activities

• Automotive Cyber-Physical Systems graduate-level course at UNC Chapel Hill.

(http://www.cs.unc.edu/~anderson/teach/comp790a/)

- Autonomous Driving: Moving from Theory to Practice graduate-level course at UNC Chapel Hill. (<u>http://need4speed.web.unc.edu</u>, https://cs.unc.edu/~anderson/teach/comp790car/)
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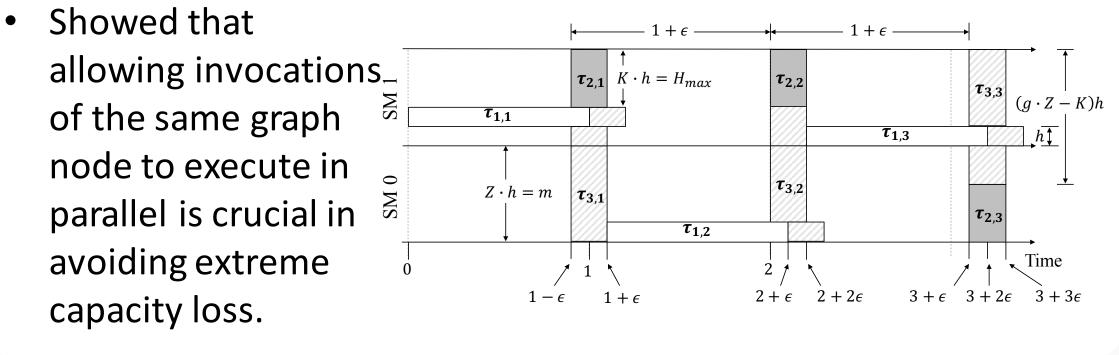
• Adapted our prior work on scheduling processing graphs and determining end-to-end graph response time bounds to apply to our fine-grained OpenVX graph, in which each node accesses either a CPU or a GPU.

Schedulability Theory

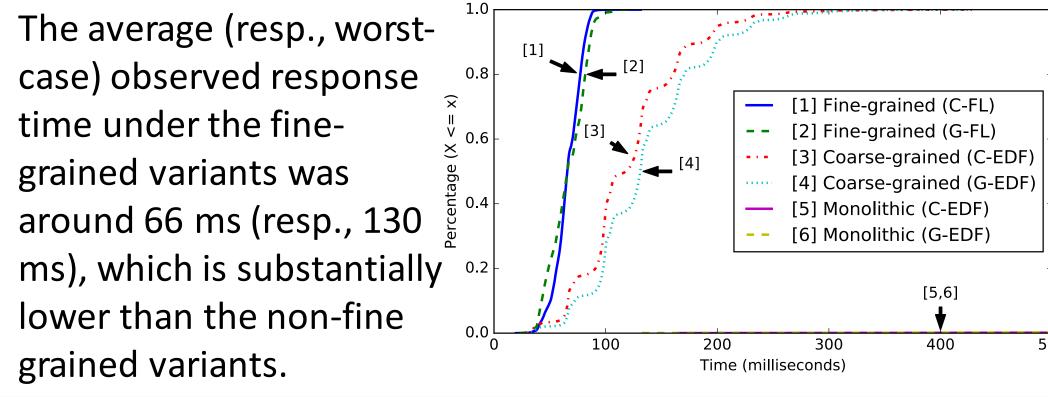
To produce response-time bound for concurrently-executed

sporadic GPU-using tasks on NVIDIA GPUs, we:

• Provided new analysis for determining response-time bounds for GPU computations. We showed how to compute such bounds for recent NVIDIA GPUs by leveraging recent work by our group on the functioning of these GPUs.



With respect to schedulablity, the monolithic and coarsegrained variants could not even come close to supporting all six cameras (i.e., DAGs), while both fine-grained variants can.



	Monolithic	Monolithic	Coarse-Grained	Coarse-Grained	Fine-Grained	Fine-Grained
	G-EDF	C-EDF	G-EDF	C-EDF	G-FL	C-FL
Analytical Bound (ms)	N/A	N/A	N/A	N/A	542.39	477.25
Observed Maximum Response Time (ms)	170091.06	243745.21	427.07	428.50	125.66	131.43
Observed Average Response Time (ms)	84669.47	121748.05	136.57	121.52	65.99	66.06