



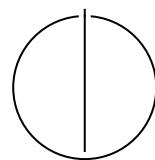
SCHOOL OF COMPUTATION,
INFORMATION AND TECHNOLOGY —
INFORMATICS

TECHNISCHE UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

GPU Coroutines in Autonomous Driving

Jaden Rotter





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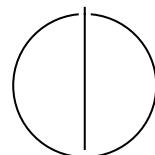
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I confirm that this bachelor's thesis is my own work and I have documented all sources and material used.

Munich, Submission date

Jaden Rotter

Acknowledgments

Abstract

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1 Introduction

Autonomous driving presents a formidable challenge in computing, requiring complex high-performance workloads that heavily rely on GPUs, yet traditional scheduling techniques fail to deliver the necessary predictability and reliability demanded by real-time systems. Graphics Processing Unit (GPU) hardware is optimized for maximizing throughput, a focus that compromises low-latency performance critical for real-time applications. Similarly, traditional GPU scheduling methods do not consider the strict deadlines essential for real time systems, particularly under conditions of GPU contention, where multiple tasks compete for limited computational resources. This thesis will implemented an approach to GPU scheduling using coroutines on persistant threads to reduce latency variability and address contention issues, ultimately delivering the predictability and reliability necessary for real-time autonomous driving applications.

1.0.1 Necessesity of GPUs in Autonomous Driving

Recently, GPUs have revolutionized data processing with their ability to handle massive amounts of data and execute highly-parallelized computations. Previous data processing systems, which used traditional CPUs, by contrast, relied on a multiple instruction multiple data (MIMD) architecture that excels at handling complex control logic at high frequencies by executing different instructions on seperate data streams concurrently. However, for tasks that require the repeated execution of singular instructions such as large-scale data processing workloads, CPUs are burdened by the overhead of the complex control logic, where a simpler, more parallel design would be more effective. GPUs, created to overcome this limitation, use a single instruction multiple thread (SIMT) architecture with thousands of simpler, slower threads executing simultaneously. The parallelism provided by the SIMT model allows a far higher throughput that outperforms CPUs. Here, each data element is processed by its own thread, allowing the same instruction to be executed simultaneously across numerous data streams.

Higher data processing performance is vital to autonomous systems, which rely extensively on machine learning tasks and sensor data processing. In autonomous systems a multitude of modules require deep learning, a machine learning technique,

to automatically extract patterns, such as computer vision, and make decisions. Deep learning, inspired by the structure of the human brain, is composed of layers of numerous interconnected, identical nodes called neural networks. Neural network models rely on mathematical operations between different neighboring layers to perform inference, essentially the prediction making or recognition process. The layers are represented as matrices, which then get multiplied and convoluted with one another and are used by specialized functions, called activation functions, to introduce non-linearity. With very large neural networks with thousands or millions of nodes, the inference computation is repetitive and slow. The capability to execute these repetitive workloads concurrently across different dataset makes GPUs fundamental to performance in tasks using complex neural networks. Furthermore, GPUs are necessary to process the data rate produced by high-bandwidth, high-frequency sensors used in autonomous driving. The parallelism in GPUs makes them the ideal platform over CPUs for deep learning and data processing tasks, tasks fundamental for autonomous driving systems.

1.0.2 Autonomous Driving as a Real Time System

Real time systems, such as autonomous driving, are designed with strict timing constraints in mind, to ensure predictable and deterministic behavior. They use a concept of deadlines, which are subdivided into soft and hard-deadlines. Hard deadlines are critical and a failure leads to the systems failure or unsafe conditions. For example, in autonomous driving, collision avoidance with another vehicle and brake activation are hard deadlines. If these deadlines are not met, the safety of the passengers and the system is at risk. On the other hand, soft deadlines are not critical and missing these deadlines degrades performance, but does not cause system failure. In autonomous driving, this would show in route planning and navigation updates, where a delay would lead to suboptimal paths, but safety is not compromised. Real time systems need to be capable of effectively and efficiently switching from lower priority tasks, soft deadline tasks, to high priority, hard deadline tasks, to ensure the safety both for the passengers and nearby individuals.

1.0.3 GPU weaknesses in Real Time Systems

Given the reliance on GPUs in autonomous driving systems for data processing and machine learning, they need to meet the strict timing requirements of real-time applications, which is lacking under current scheduling methods. GPU tasks are traditionally queued and scheduled based on availability to optimize for high throughput applications like graphics rendering and offline machine learning training. These tasks run to completion, similar to a batch system, meaning multiple tasks, such as the different

modules in autonomous driving execute sequentially. Thus, depending on the current workload for the GPU, the execution time and latency can vary, which poses a safety risk. To adapt GPUs to the requirements of real time systems, while maintaining the advantages they provide in processing power, the scheduling of these systems needs to support asynchronous programming.

1.1 Background

1.1.1 Asynchronous Programming and Coroutines

Asynchronous programming allows execution to pause and switch tasks, enhancing responsiveness, improving determinism and reducing latency.

These limitations make existing GPU scheduling mechanisms unsuitable for real-time applications like autonomous driving, where deadlines need to be met to ensure the safety of the system and passengers.

1.1.2 Autonomous Vehicles

Autonomous driving systems, such as self-driving cars, are subdivided into several modules, perception, localization, mapping, planning and control, which all rely on massive data processing and machine learning, to help the system to understand its environment, plan its trajectory and drive without any human help. Perception gathers and interprets vast amounts of data from numerous sensors, such as Light Detection and Ranging (LiDAR) sensors, cameras, radar, and ultrasonic sensors, to identify and classify surrounding objects. After perception, localization and mapping use a Simultaneous Localization and Mapping (SLAM) algorithm to build maps and determine the vehicle's precise location within its environment and the generated map. Using the foundation set by localization and mapping, path planning determines the vehicle's trajectory from its current location to a target destination, while respecting traffic laws and avoiding obstacles. Lastly, control actively follows the trajectory and sets the speed, steering and braking required for the planned path. Autonomous driving systems are constantly computing each of these modules based on updates in the surroundings, which requires significant computational resources to maintain a low latency.

Specifically, these modules require large amounts of data to accurately compute , which are based in deep learning, a machine learning technique that demands vast amounts of computational resources. In perception, deep learning models, particularly CNNs identify objects, lane markings, pedestrians, vehicles, and traffic lights from the raw sensor data. Beyond perception, deep learning enhances localization by

refining sensor fusion techniques, improving accuracy in determining the vehicles position. Furthermore, deep learning also supports planning and control, through reinforcement learning and predictive models to optimize trajectories. The real-time nature of these components are needed to reduce the latency, which requires these models to continuously be updating their predictions as new sensor input arrives and the vehicle moves. This places a high demand on the hardware, requiring high-performance accelerators to process vast amounts of data efficiently. To meet these requirements, these computations are scheduled on to a GPU, which provides the high degree of parallelism required by the vast amount of data and computations within autonomous driving.

1.1.3 Asynchronous Programming

1.1.4 Real Time Systems

1.1.5 Autonomous Driving Systems

1.1.6 GPUs

1.1.7 NVIDIA Tesla V100 Architecture

For the purpose of this thesis, the NVIDIA Tesla V100 accelerator, which uses the Volta GV100 GPU architecture, was selected due to its availability and high-performance computing capabilities. At the core of its execution model is the warp, a group of 32 threads executing in SIMD fashion. Each warp is scheduled and dispatched within one of the 4 processing partitions of a Streaming Multiprocessor (SM). The warp scheduler and warp dispatcher each handle 32 threads per clock cycle. Within each SM partition, there are Tensor Cores for deep learning, 64 bit-floating point (FP) cores, Load/Store (LD/ST) units, a register file, and SFUs for mathematical functions such as sine and square root. Additionally, each partition contains 16 Cuda cores, which can execute both FP 32 bit and integer (INT) 32 bit instructions, but not simultaneously. Each partition has its own L0 instruction cache, while all partitions share a L1 instruction and data cache. A SM can support up to 64 concurrent warps, allowing a maximum of $64 * 32 = 2048$ threads per SM. At a higher level, two SMs are grouped to form a Texture Processing Cluster (TPC). The Tesla V100 GPU consists of six GPCs, each containing seven TPCs, resulting in a total of 84 SMs across the chip. This hierarchical organization, from warps to SMs, TPCs, and GPCs, enables the Tesla V100 to efficiently handle massively parallel workloads, making it well-suited for high-performance computing and deep learning applications.

1.2 Motivation

In autonomous driving and other real time system tasks, GPUs are essential for data processing and machine learning; however, existing GPU scheduling techniques fail to meet the strict timing requirements of real-time applications. GPU tasks are traditionally queued and scheduled based on availability to optimize for high throughput applications like graphics rendering and offline machine learning training. These tasks run to completion before switching tasks, meaning multiple tasks, such as the different modules in autonomous driving cannot efficiently share resources. Depending on the current workload for the GPU, execution times and latency can vary. These limitations make existing GPU scheduling mechanisms unsuitable for real-time applications like autonomous driving, where deadlines need to be met to ensure the safety of the system and passengers.

2 Objectives

The objective for this thesis is to develop, implement and evaluate a persistant thread with coroutine based scheduling approach for GPU threads to improve real-time performance by ensuring a predictable scheduling behavior.

This requires analyzing the limitations of existing GPU scheduling techniques, which, due to their batch processing design, lack the ability to perform task switching. To address this, a new scheduling mechanism will be designed that allows GPU execution to be halted by yielding, temporarily giving the processing resources to a different process. Resuming execution will involve saving and restoring the executing state for the previous process. Enabling GPUs to yield and switch between processes dynamically will improve responsiveness and reduce latency. The end completed solution will be a library that can be used with an API to automatically use coroutines on persistant threads.

2.0.1 Measurement and Evaluation

To measure the success of a coroutine based solution, the latency of new time sensitive task scheduling and deadline success will be evaluated. Unfortunately, this extra overhead, required to halt and restart cuda kernels, will result in overall weaker performance. Furthermore, the success will be measured on the implementability and ease of use to programm with and combine into Apollo, an open source autonomous driving platform.

3 Literature Review

3.1 GPU Partitioning

3.2 a

4 Proposed Approach

4.1 Section

The proposed solution will use a library with an API to implement coroutines on persistent threads. When a new task, from the CPU, is scheduled, the task must actively notify the GPU that a new task exists and the GPU needs to halt. This signaling will happen, by using GPU flags that can be set and evaluated or potentially through a maximum latency approach. The maximum latency approach, will maintain a maximum latency between when a task is scheduled onto the GPU and when the task needs to start, by periodically checking for new tasks. Next a mechanism to saving the thread state and resetting the thread state will be implemented. The thread state consists of the Program Counter (PC), thread register values, and memory state, which consists of thread private memory, warp and block level memory, and the persistant state. These values must be stored in the global memory and then resused to restore execution. Furthermore, to prevent deadlocks a synchronisation mechanism needs to be developed, to disallow deadlocks. If a GPU kernel uses a syncThreads() call and a coroutine attempts to yield it at that point, a deadlock will occur.

Abbreviations

GPU Graphics Processing Unit

CPU central processing unit

MIMD multiple instruction multiple data

SIMT single instruction multiple thread

GPC Graphics Processsing Cluster

TPC Texture Processing Cluster

SM Streaming Multiprocessor

FP floating point

INT integer

LD/ST Load/Store

SFU special function units

LiDAR Light Detection and Ranging

CNN Convolutional Neural Network

PC Program Counter

SLAM Simultaneous Localization and Mapping

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