Mobility CPS in the Cloud and Latency Evaluation

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***Abstract*—Visione-based object detection using camera sensors is an essential piece of perception for autonomous vehicles. Various combinations of features and models can be applied to increase the quality and the speed of object detection. A well-known approach uses histograms of oriented gradients (HOG) with deformable models to detect a car in an image [12]. A major challenge of this approach can be found in computational cost introducing a real-time constraint relevant to the real world. In this paper, we present an implementation technique using graphics processing units (GPUs) to accelerate computations of scoring similarity of the input image and the pre-defined models. Our implementation considers the entire program structure as well as the specific algorithm for practical use. We apply the presented technique to the real-world vehicle detection program and demonstrate that our implementation using commodity GPUs can achieve speedups of 1.5x to 3x in frame-rate over sequential and multithreaded implementations using traditional CPUs.**

***Index Terms*—Cloud Computing; Smart Devices; CPS**

I. Introduction

Grand challenges of cyber-physical systems (CPS) include a high computational cost of understanding the physical world. Object detection is one of compute-intensive tasks for CPS. For example, an autonomous vehicle needs to detect and track other vehicles by itself. Current autonomous driving technologies [6], [11], [17] tend to rely on active sensors such as GPS, RADAR, and LIDAR [9], [15] together with very accurate pre-configured maps, but the use of passive camera sensors is becoming more practical due to recent advances in computer vision [2]–[4]: vision-based object detection can be applied for various ranges and orientations. In particular, histograms of oriented gradients (HOG) [2] features provide reliable high-level representations of an image underlying many state-of-the-art object detection algorithms [3], [5], [14], [16], [18]. However, a major concern of HOG-based object detection remains in computational cost.

Previous work on the implementation of HOG-based object detection are limited to either hardware implementations [7], [8], [10] or specific parts of HOG algorithms [1], [13]. There is even no quantitative investigation of what implementation issues could prevent HOG-based object detection from being deployed in real-world applications. Given recent innovations in commodity hardware technology such as multicores and graphics processing units (GPUs), it is worth exploring if the current state of the arts meets computational requirements of cutting-edge object detection implementations.

Contribution: This paper presents GPU implementations of HOG-based object detection in consideration of real-world applications using deformable part models [3]. While this is a popular vision-based object detection approach, what remains an open question is a genelized programming technique and a quantification of performance characteristics for practical use. We begin with an analysis of traditional CPU implementations to find fundamental performance bottlenecks of HOG-based object detection. This analysis reasons about our approach to GPU implementations where we parallelize compute-intensive blocks of the object detection program using the GPU step by step to minimize its makespan. The experimental results obstained from a real-world car detection program using a commodity GPU show that the GPU outperforms the CPU by 1.5x to 3x in frame-rate, while another 2x improvement would be needed at least to deploy in the real world.

Organization: The rest of this paper is organized as follows. Section **??** describes the assumption behind this paper. Section **??** presents an analysis of HOG-based object detection and our GPU implementation technique. Section **??** evaluates the performance benefit of our technique over traditional CPU implementations. This paper concludes in Section **??**.

II. Concept

In this paper, we adovocate a concept of mobility CPS in the cloud. Many mobility CPS applications are battery-operated. They cannot accommodate large power consumers unless they equip special battery facilities. Integrating cloud technology allows computations and data to be offloaded over the network and we are freed from power consumption issues.

A. Big Data

Grand challenges of mobility CPS include the modeling of the physical world that underlies the real-time understanding of the physical world including enviromental perception and motion control. The modeling of the physical world requires accumulative collection of real-world data. This is often referred to as "Big Data" on the recent trend.

Fig. 1 illustrates an example of collecting automotive data through the on-board diagnosis (OBD) connectors as well as

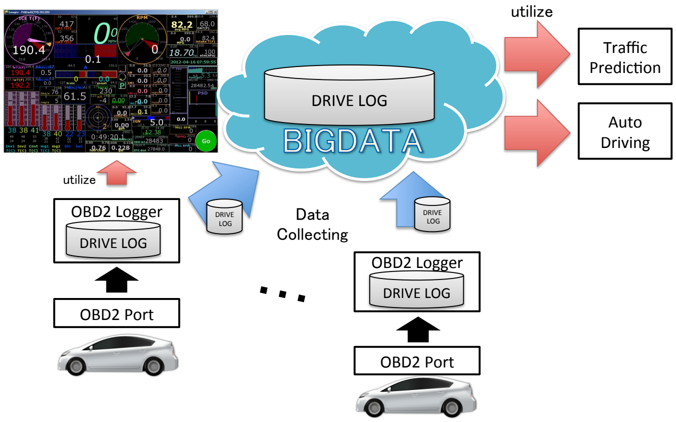

Fig. 1. Collecting automotive data.

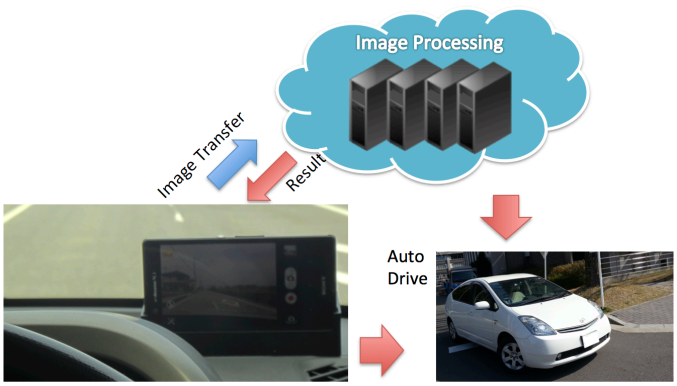

Fig. 2. Networked image processing.

environmental and human data. We are building this system using commodity products. The automotive data can be obtained as CAN bus data while the environmental and human data can be captured using mobile devices such as smartphones. While the data volume is a challenging issue and especially a cummulative collection of laser sensor data and camera images produces a significant amont of data, this is more or less a typical information and communication technology (ICT) problem but not necessarily associated with CPS and latency matters. Currently we store the collected data in a vehicular computer and move them to database systems and storage servers offline. Although this approach is sufficient to collect mobility data, it means that CPS applications need to communicate with these Big Data systems at runtime to adapt to the dynamically changing physical-world environment. We will discuss these issues in Section II-B and II-C.

B. Perception

C. Control

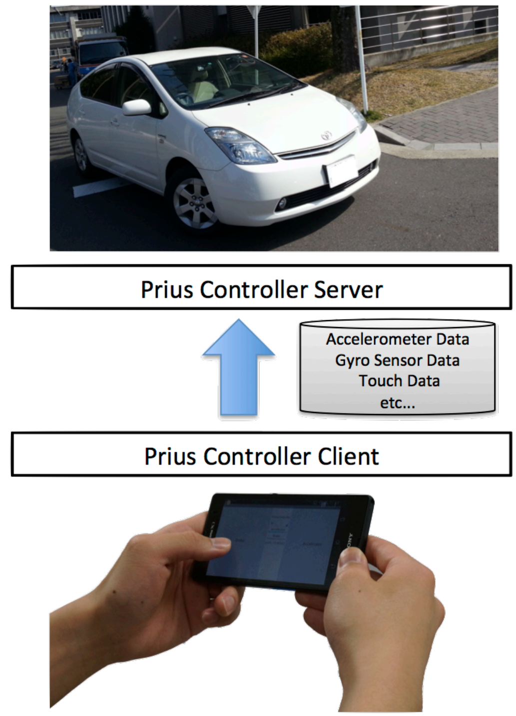

Fig. 3. A smartphone application for remote vehicle control.

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