Prototyping Commodity ICT for Mobility CPS

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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 [3]. 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

Mobility is an essential piece of our life. In recent years, transportation systems and automobiles are becoming more and more intelligent underlying high-efficient mobility of the societal infrastructure. Such innovations in mobility will reduce car accidents, remove humanś stress, improve traffic throughput, and create new markets. To this end, the next-generation mobility technology is expected to achieve a tight coordination of computer systems and physical elements, often referred to as cyber-physical systems (CPS), facilitating a cyber-understanding of the physical world. A core challenge to this mobility CPS, however, is a power and space constraint of each mobility component. For example, moving vehicles cannot accommodate rich computer systems due to the limited battery power. Particularly the computational cost with respect to understanding the physical world is very high and the computing capability of current vehicular systems is woefully inadequate. In order to address this trade-off, mobility CPS must seek for a cooperative solution with advanced information and communication technology (ICT) such as cloud computing.

A good example of compute-intensive mobility CPS applications is an autonomous vehicle [1], [2], [4]. It must recognize roads, traffic signs, surrounding vehicles, and pedestrians in real-time. An autonomous vehicle in the current state of the art tends to use laser sensors and/or cameras for those environmental perception tasks. The laser sensors can detect object edges as a set of 3-D points by hardware, reducing the computational requirement imposed on the vehicular system software, but are generally very expensive way beyond consumer electronics prices. On the other hand, the cameras are less expensive in price but are available at the expense of computational cost, because image processing is highly compute-intensive. It would require a rich set of multicore CPUs and hardware accelerators such as GPUs to meet the desired frame rate. Unfortunately these devices may not be affordable for battery-operated vehicular systems due to power consumption issues. As mentioned earlier, therefore, we should seek for a possibility of leveraging cloud computing technology to offload compute-intensive tasks onto high-performance computing (HPC) servers over the network. A question raised herein is "what is the overhead of offloading computation and associated data to the cloud?" If this overhead is acceptable, commodity ICT platforms will be a strong basis for mobility CPS applications.

Contribution: We present a prototype implementation of commodity ICT platforms for mobility CPS applications to quantify the overhead of offloading computation and data to the cloud. Specifically we use a smartphone as an example of commodity ICT platforms to capture images and control an autonomous vehicle as an example of mobility CPS applications. The overhead of transferring images over the network governs the frame rate of image processing in the cloud while that of transferring control commands determines the minimum feedback-control period of autonomous driving. We demonstrate that the bottleneck of networked image processing can be found in the computation time itself rather than the network communication overhead. We also find that the average network throughput of commodity ICT is sufficient to execute autonomic control but the worst-case latency must be bounded to provide stability. This is a useful insight into a coordination of commodity ICT and mobility CPS.

Organization:

II. Basic 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

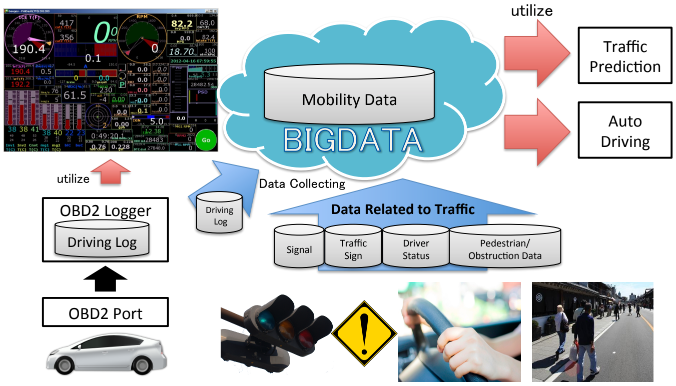

Fig. 1. Collecting automotive and environmental data.

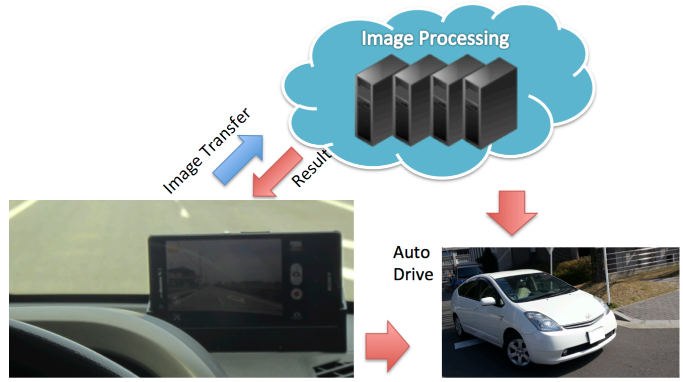

Fig. 2. Networked image processing.

technology allows computations and data to be offloaded over the network and we are freed from power consumption issues. For simplicity of description, we present our concept in the context of autonomous driving, but it is highly applicable for other mobility CPS applications.

Grand challenges of mobility CPS include a modeling of the physical world that underlies a real-time understanding of the physical world including enviromental perception and motion control. This modeling of the physical world requires accumulative collection of real-world data, often referred to as “Big Data”.

Fig. 1 illustrates an example of collecting automotive data through the on-board diagnosis (OBD) connectors as well as environmental data. We are building this system using commodity ICT products. The automotive data can be obtained through the CAN bus, while the environmental data can be captured using mobile devices such as smartphones. These data sets can actually be shared with a lot of mobility CPS agents. Such “Big Data” trends also encourage the concept of mobility CPS in the cloud. Since the data sets are stored in the cloud, each mobility CPS agent needs to access the network. For example, we can store a very large global trained data set [3] for anonymous agents to perform image recognition. The first step towards this approach is to understand the scale of latency and overhead imposed on cloud computing in real-time.

III. Prototyping

The computional cost of real-time perception in mobility CPS is highly expensive. The perception algorithm is often computationally complex and the volume of input data from laser sensors and cameras is not afforable for mobile embedded systems.

IV. Evaluation

We now evaluate the data transfer overhead in the context of cloud-based autonomous driving. We assume that autonomic control and environmental perception are provided in the remote server, but they are not within the scope of this paper. What we focus on in this experiment is the measurement of the data transfer overhead.

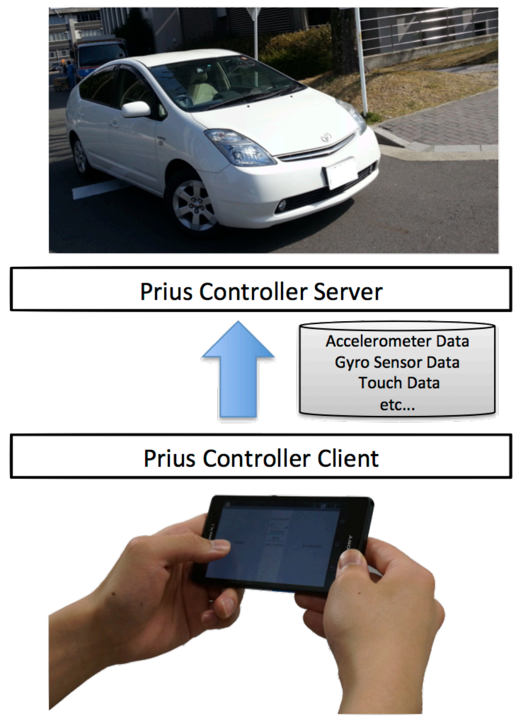

Fig. 3. A smartphone application for remote vehicle control.

A. Control Command Transfer

This experiment measures the transfer time taken to send control commands to the vehicle from a smartphone. The commands control the steering, accel, and brake of the vehicle. The steering angle is determined by the gyro sensor data while the accel and break strokes are manipulated by the graphics user interface of the Andrive application. We use the HTC J butterfly Snapdragon S4 Pro (APQ8064@1.5GHz, Quad Core) for a testing smartphone.

Fig. 4 shows the transfer time for control commands using WiFi. Note that the PC server sends back an acknowledge message to the smartphone client every time the commands are received.

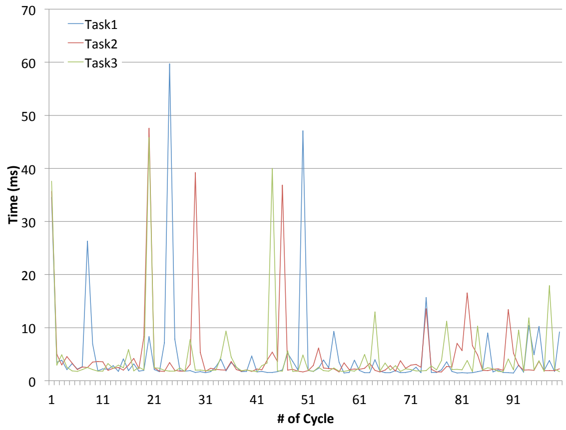

Fig. 4. The synchronous transfer time for control commands using WiFi.

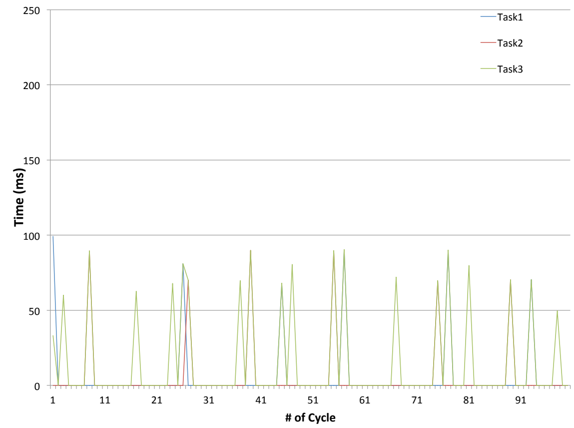

Fig. 7. The asynchronous transfer time for control commands using LTE.

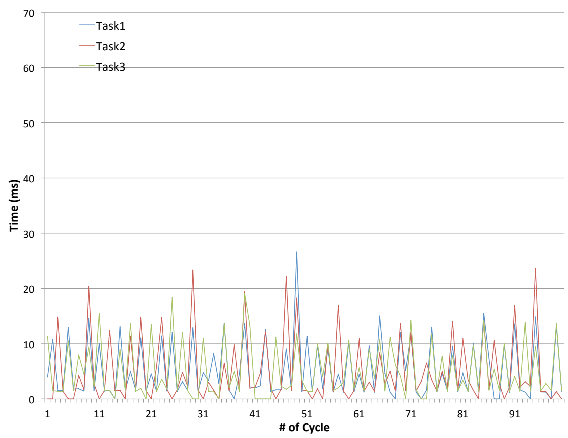

Fig. 5. The asynchronous transfer time for control commands using WiFi.

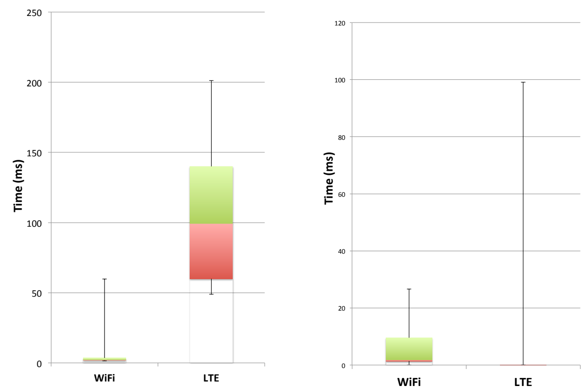

Fig. 8. Summarized box plotting of the transfer times.

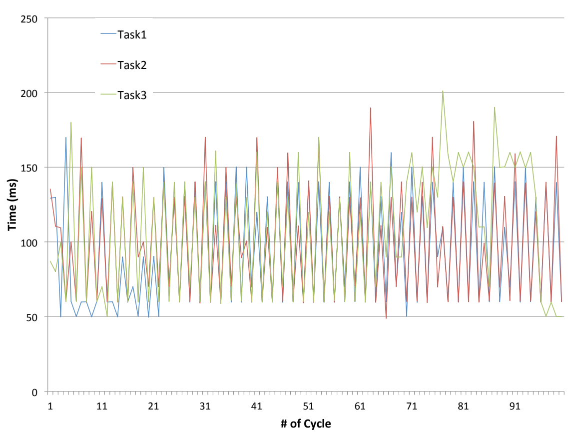

Fig. 6. The synchronous transfer time for control commands using LTE.

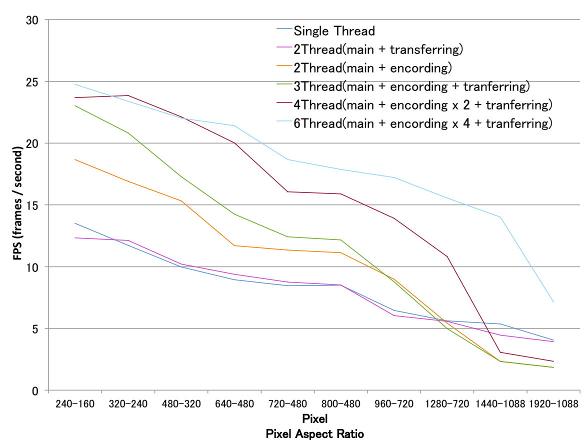

Fig. 9. The frame rate of networked image processing using WiFi.

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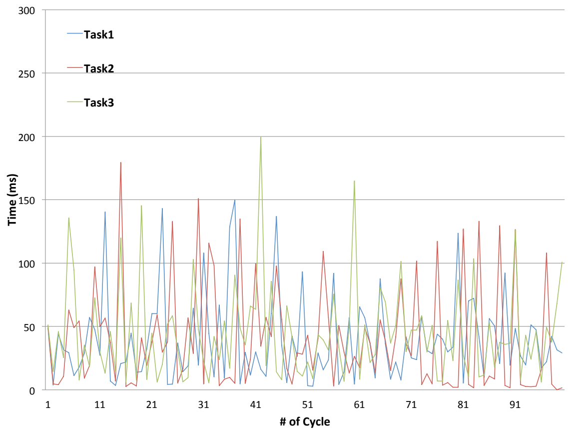

Fig. 10. The arrival time of networked image processing using WiFi.

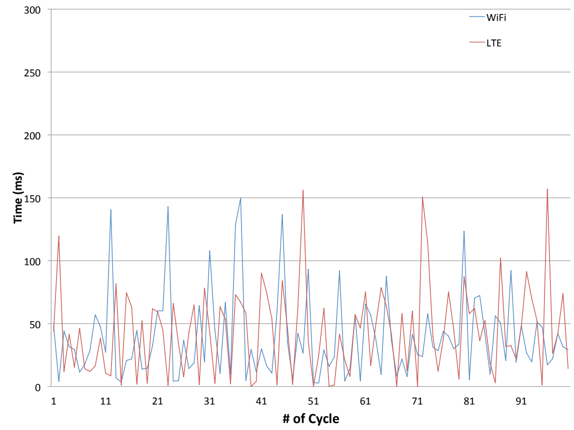

Fig. 13. A comparison of the arrival times.

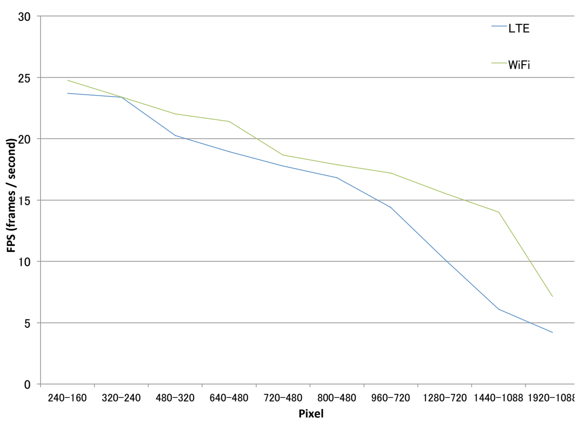

Fig. 11. The frame rate of networked image processing using LTE.

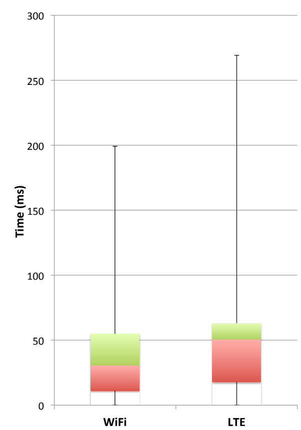

Fig. 14. Summarized box plotting of the arrival times.

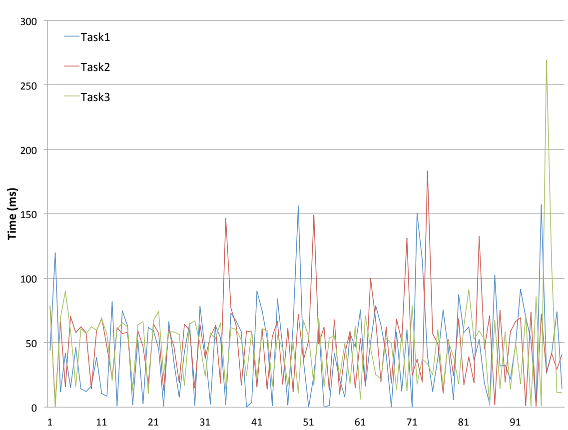

Fig. 12. The arrival time of networked image processing using LTE.

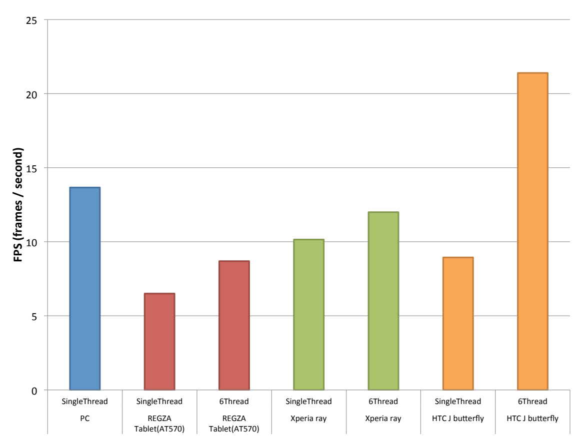

Fig. 15. Performance differences of a smartphone and PC.

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