RoadLab: An In-Vehicle Laboratory for Developing On-Board i-ADAS

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Abstract

According to the WHO (World Health Organization), world-wide deaths from injuries are projected to rise from 5.1 million in 1990 to 8.4 million in 2020, with traffic-related incidents as the major cause for this increase. Intelligent, Advanced Driving Assistance Systems (i-ADAS) provide a number of solutions to these safety challenges. We developed a scalable in-vehicle mobile i-ADAS research platform for the purpose of traffic context analysis and behavioral prediction designed for understanding fundamental issues in intelligent vehicles. We outline our general approach and describe the in-vehicle instrumentation. We present a number of research challenges and early results, as we outline future directions.

I. Introduction

Driving is an essential aspect of our economy which directly or indirectly impacts a number of critical economic factors. In North America, there were 6 million accidents, 1.7 million injuries, and 39,000 fatalities in 2006 [1]. Yet the simplest of driving assistance systems such as enhanced stability control (ESC) may reduce single-vehicle crashes by 29 to 35 percent [2]. Even with low penetration levels (5 to 10 percent), the safety of every vehicle increases. In addition, vehicle curb weight is a significant fuel consumption factor. Hypothetically, a crash-less car could be made much lighter without endangering its occupants. As of today, such vehicles cannot be manufactured due to enforced crash-safety ratings. Compounding the problem, traffic congestion is a growing problem world-wide as car ownership continues to skyrocket. In a typical congestion situation, an air-view of the traffic reveals that vehicles occupy only roughly 10 percent of the available pavement. ADAS technologies could improve this radically by automating longitudinal vehicle control, for instance. Such systems could increase the density of traffic with vehicles following each other closely and safely, alleviating the need to extend current highway infrastructures [3]. Also of significance is the fact that the average age in western countries is on the rise. While this should not be a problem unto itself, it has nonetheless been established that a decline in cognitive and motor abilities impacts the safety of drivers and others around them [4], [5].

In this contribution we address the physical design and implementation of an in-vehicle laboratory for the development of i-ADAS. Our approach, while sharing common elements with those of others, is unique in several ways. First, we designed a portable instrumentation requiring no modification to the vehicular platform, using low-cost off-the-shelf components that are widely available. Second, our on-board computational approach rests on scalability. That is to say, additional computing power can easily be added to the current instrumentation, without any modifications to the existing system. This of course is a core requirement, as algorithms must be run in real-time. Third, our approach integrates the driver in the system as an inherent behavioral agent, in the aim of understanding and predicting driving actions.

II. Related Literature

While injuries per driven kilometer are in decline in developed countries [1], a reverse trend can be observed elsewhere in the world, especially in regions where car ownership is rising quickly. In addition, further significant gains in traffic safety in developed countries seem only possible via ADAS, since the impact of other forms of safety improvements have begun to plateau [6].

Advanced Driving Assistance Systems are generally designed to support decision making by providing ergonomic information on the driving environment, such as the presence of surrounding vehicles, potential hazards, and general traffic conditions. A large array of sensing devices and data fusion strategies have been devised and deployed to create effective ADAS. Sensing may be performed with radar [7], [8], lidar [9], or laser range finders [10]. However a majority of ADAS rely principally on vision systems supported by other sensor modes [11]. With such a variety of sensor modalities and hard real-time constraints, fusion becomes central to ADAS and the current literature reflects this fact in the large number of contributions that approach data and knowledge fusion in this context [12], [7], [13], [14]. Alternatively, several functions of ADAS may be realized using vehicle-to-vehicle (V2V) wireless communication protocols and

Global Positioning Systems (GPS). Examples include the diffusion of traffic information, [15], [16], collision warning systems [17], [18], lane changing assistance [19], and tracking neighboring vehicles [20].

While research on ADAS may integrate a number of different functions such as forward collision detection and lane departure tracking [21], little attention is devoted to the monitoring of events and factors that directly concern the driver of the vehicle. It is only recently that cognitive aspects have been considered as a legitimate part of intelligent ADAS [22]. Since 95 percent of all accidents are caused by human error, it is crucial that these aspects of driving be a central part of intelligent ADAS [23]. Keeping the driver as an active participant in the feedback mechanisms allows for providing contextually motivated informational support and offers immediate applications for enhancing safety [24].

The extended possibilities of integrated, intelligent ADAS are very relevant research areas as they do not intend to replace the driver as much as to assist in the process of driving safely. As it has been pointed out by Petersson *et al.* [24], what remains to be automated to reach the state by which vehicles become completely autonomous in a practical manner turns out to be difficult and elusive in everyday driving situations. In light of this, it is our belief that driver support through i-ADAS can be deployed more readily, with consequent socio-economic benefits.

III. Layered Approach to Intelligent Vehicles

The next generation of i-ADAS will require extensive data fusion and analysis processes owing to an ever increasing amount of available vehicular information. In this context a layered approach is best suited for real-time processing. In particular, such an approach enables bringing real-time data from sensors to a common level of compatibility and abstraction which significantly facilitates fusion and analysis processes. Our proposed computational model consists of four layers, with increasing levels of data abstraction (see Figure 1). The innermost

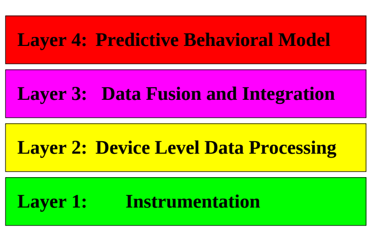

Fig. 1. *The four layers comprising the data processing strategy on-board the instrumented vehicle.*

layer consists of the hardware and software required to capture vehicle odometry, sequences from visual sensors, and driver behavioral data. The second layer pertains to hardware synchronization, calibration, real-time data gathering, and vision detection processes. The third layer is where the data is transformed and fused into a single 4-dimensional space (x, y, z, t). The last layer makes use of the fused data to compare driver behavioural data with models of behaviour that are appropriate given current odometry and traffic conditions.

A. Instrumentation

Contemporary vehicles equipped with On-Board Diagnostic systems (OBD-II) allow vehicle sensors to report on current status, and constitute the interface through which odometry is made available in real-time. Since 2008, the CANbus protocol[1] has become mandatory for OBD-II. This standardization simplifies the real-time capture of vehicle data. OBD-II to USB hardware interfaces with appropriate drivers are now common devices used to feed vehicle-related information to on-board computers or similar devices. The available information relevant to i-ADAS applications include current speed and acceleration (longitudinal and lateral), steering wheel rotation, state of accelerator and brake pedals, and independent wheel speed, which are real-time data captured at frequencies generally comprised between 20 and 200Hz. These elements provide the information that is required to understand the maneuvers effected by the driver.

In addition, several vision systems must instrument the vehicle in order to appropriately monitor the immediate environment (lanes, other vehicles, pedestrians, obstacles, etc) and the behavior of the driver (gaze direction, level of attention, etc). These hardware systems must be capable of high sampling rates (30Hz or more) such that sufficient accuracy in image processing and automated vision processes is achieved. It is useful to keep in mind that the position of a vehicle moving at 120 kph changes by 33 meters every second.

Similar observations apply concerning the changes in visual gaze direction (known as saccades) as they occur very rapidly. For this reason, vision hardware monitoring the gaze direction of the driver must have sufficiently dense sampling rates as to allow for deriving driver intentionality prior to the execution of the anticipated behavior [25]. This part of the vehicle instrumentation is realized with commercial hardware and software[2] from which data such as eye gaze direction, vergence distance, and saccade events are obtained at a frequency of 60Hz.

Also part of the instrumentation layer is a GPS device which is used by Vehicle-to-Vehicle (V2V) communications systems to provide other near-by instrumented vehicles with knowledge of traffic conditions beyond the range of their visual sensors.

Last but not least, on-board computing capabilities must also be sufficient to process the sum of incoming data in real-time. To this end we have designed and

[1]The CANbus (Controller Area Network bus) provides micro-controllers with the means to communicate with each other within a vehicle.

[2]FaceLAB 5^{TM} implements our instrumentation for eye tracking.

assembled a computer for real-time data processing and fusion consisting of 16 cores, each running at 3.0GHz, with 16GB of internal memory and a 128GB Solid State Drive (SSD), with Linux Debian 5.01 as the operating system. The nodes are networked with a high-end gigabit network switch, and configured as a disk-less cluster, with the master node providing the operating system image to other nodes.

B. Device-Level Data Processing

For visual sensors, it is critical to obtain precise calibration parameters such as lens distortion, the optical center, and the external orientation of sensors with respect to each other. This calibration is required to perform stereo and to estimate distances of objects (other vehicles, pedestrians, etc.), which in turn greatly simplifies other vision-related tasks such as estimating motion, tracking, and obstacle detection. The RoadLab stereo calibration interface was designed for this process (see Figure 2). The interface is implemented using a calibration algorithm from the OpenCV 2.1 open source library based on Zhang's technique [26]. The calibration process consists of two steps. Intrinsic parameters are first estimated for each sensor and then, based on these, the extrinsic parameters for all possible sensor pairs are obtained. It is also possible to estimate the extrinsic parameters dynamically [27]. All the image frames from visual sensors are synchronized to within 125 μs. Once the synchronized frames are obtained, stereo depth maps are computed at frame rate, based on the calibration parameters (see Figure 3).

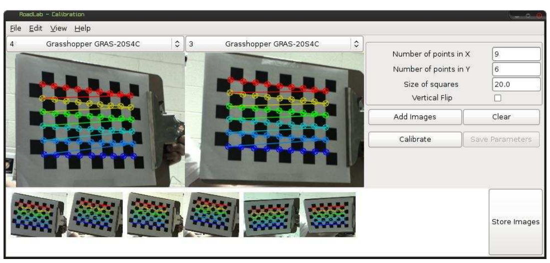

Fig. 2. *The RoadLab stereo calibration interface collects sequences of images of a calibration pattern, each with a different orientation. Both intrinsic and extrinsic parameters are estimated.*

The GPS data is obtained through `gpsd`, a GPS service daemon from `http://gpsd.berlios.de/` which provides an event-driven architecture. The data from the OBD-II/CANbus is obtained in a similar manner by creating a software layer for this purpose. Additionally, the incoming data from the instrumentation provides timestamps, allowing the system to fuse and select data elements in a synchronized fashion.

C. Data Fusion and Integration

Streams of data and video frames coming from monitoring the driver, the environment, and vehicle odometry must be placed in a suitable context for use by the behavioral prediction engine. We define a driver-centered frame of reference, in which elements of the Cognitive State of Driver (CSD) descriptor (head pose, gaze direction, blink events, lip movement), the Contextual Feature Set (CFS) descriptor (road lanes, other vehicles, pedestrians, etc), and the Vehicle State of Odometry (VSD) are transformed into, from their local sensor frames of reference (see Figure 4 for a depiction of the CSD and CFS descriptors in the context of our layered model). This is performed by using the extrinsic parameters obtained with the calibration of the visual sensors with respect to each other. With these elements fused into a single frame of reference, the current CSD, CFS, and VSO descriptors are updated at 30Hz, and made available to the behavioral prediction engine.

Two modes of operation exist at this level. A recording mode captures the data and video streams from the instrumentation for in-laboratory, off-line analysis. A processing mode which performs as an i-ADAS operating in real-time is also possible. Each sequence generated for off-line analysis obeys a strict format standard, in which the calibration data, the timestamped frames from the stereo systems, and the vehicle odometry are recorded at 30Hz.

D. Predictive Behavioral Model

Our general hypothesis stems from research demonstrating that eye movements reflect moment-to-moment cognitive processes used to locate the information needed by the motor system for producing actions in relation to the environment [25], [28], [29]. This hypothesis is the foundation for our conjecture stating that the analysis of driver gaze direction (and other facial features) fused with the knowledge of the environment surrounding the vehicle (and its odometry) lead to the possibility of predicting driving behavior for short time frames (a few seconds). To accomplish these goals, it is necessary to infer a behavioral driving agent model that puts in relation the cognitive state of the driver, the vehicle odometry, and its surrounding environment as captured by sensors. For this purpose, we devise a Real-Time Descriptor (RTD) for a moving vehicle essentially consisting of a CFS, a CSD, and a VSO descriptor.

These elements represent the knowledge required in composing an extensive RTD suited for our purposes. While we are interested in deriving practical and predictive driving agent models, it is worth noting that both the CFS and the VSO possess predictive models which are less difficult to formulate. We further propose to structure the elements of the RTD within a retroactive mechanism (see Figure 4) in which both the current and predicted descriptors (CSD, CFS, and VSO) assist in determining not only the safety level of the context derived from the current RTD, but also that posed by the predicted RTD.

At the heart of the behavioral prediction engine is a Bayesian model which takes the current CSD, CFS,

Fig. 3. *Color-coded calibrated stereo depth maps are obtained at 30Hz. The distance between the instrumented vehicle and the roadside curbs, and other vehicles, is estimated in real-time.*

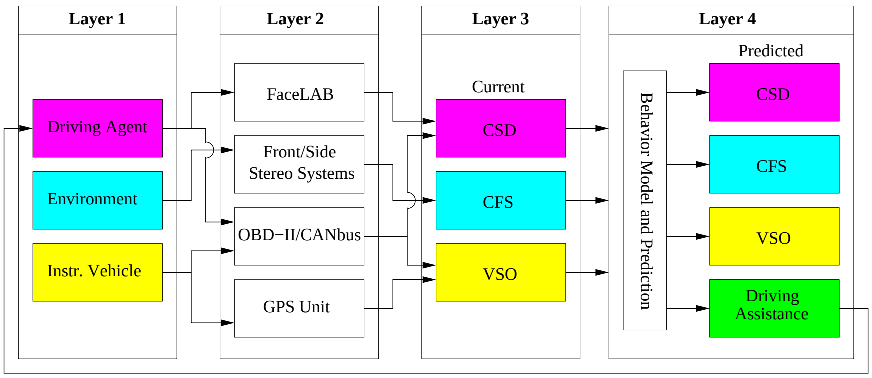

Fig. 4. *A description of the retroactive mechanism operating between the current and predicted RTDs with respect to the outlined layered approach, in which driving assistance impacts both the current and predicted behavioral state of the driving agent.*

and VSO as inputs and predicts actuation behavior of the driver in the next few seconds. It also gathers statistical information about driving decisions and errors in a Driver Statistical Record (DSR) which can be used over time to improve the prediction accuracy. The current CSD and CFS are in turn used to establish a Driver Memory of Surroundings (DMS) based on the attention level and gaze direction analysis of the driver. A General Forgetting Factor (GFF) is applied to the DMS as time elapses to reflect common characteristics of short-term visual memory. In addition, a Driver Cognitive Load factor (DCL) is inferred, based on the activities engaged by the driver, which in turn impacts the DMS, among other things.

IV. In-Vehicle Laboratory

The design of the instrumented vehicle follows principles of sensor portability and computing scalability. Sensor portability is achieved by using vacuum devices to attach the instrumentation equipment to the the interior glass surfaces of the vehicle (see Figure 5), such as stereo camera rigs, LCD screens, and GPS units without the need to perform permanent modifications to the vehicle. The odometry is obtained from the OBD-II outlet located under the dashboard on the driver's side of the vehicle.

Each minute, the sensory equipment sends 2 to 6GB of data to the on-board computer. With such large amounts of data to process, the computing equipment was designed with scalability as a guiding principle. For this purpose, A disk-less cluster arrangement was chosen essentially to provide the option of adding computing nodes as necessary. Currently, the on-board computer is composed of 16 computing nodes distributed over four boards networked with a gigabit switch. The nodes and the switch are contained inside a portable server case which in turn can be installed on the back seat or in the trunk of the vehicle.

The computer and instrumentation are powered with a 1500W inverter connected directly to the battery of the vehicle. The instrumentation can be run continually without battery drainage.

V. Research Challenges

The hardware and software instrumentation of the research vehicle provides the foundation for addressing relevant questions pertaining to driving and its associated risks, such as:

- assessing the cognitive state of drivers in order to predict maneuvers within a defined time frame;
- supporting driver decisions by providing advance information and warnings that are related to the context of current and predicted maneuvers along with traffic conditions in an ergonomically acceptable fashion;
- analyzing long-term driving patterns in ways as to understand the most common causes of driving errors [30];

Fig. 5. *The RoadLab in-vehicle laboratory:* **a) (left):** *on-board computer and LCD screen,* **b) (center):** *dual stereo front visual sensors,* **c) (right):** *side stereo visual sensors.*

- determining what constitutes an acceptable Human Machine Interface (HMI) which minimizes driver distractions;
- developing short range vehicular networking technologies to relay traffic information and to augment the effective range of on-board sensors.

In addition to researching these fundamental aspects of advanced driving assistance systems, our current in-vehicle research platform enables us to test and validate retroactive models consisting of current and predicted RTDs and their core descriptors (CSD, CFS, and VSO).

VI. Conclusion and Directions

We have developed a vehicle-independent, portable and scalable in-vehicle instrumentation for i-ADAS. Our motivation to develop this in-vehicle research platform stems from the observation that while injuries per driven kilometer are in decline in developed countries, a reversed trend can be observed elsewhere in the world [1]. Technologies such as i-ADAS have the potential to significantly reduce the burden of vehicle accidents and their consequences.

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