Data Recording for Remote Monitoring of Autonomous Vehicles

Rong-Terng Juang

Abstract—Autonomous vehicles offer the possibility of significant benefits to social welfare. However, fully automated cars might not be going to happen in the near further. To speed the adoption of the self-driving technologies, many governments worldwide are passing laws requiring data recorders for the testing of autonomous vehicles. Currently, the self-driving vehicle, (e.g., shuttle bus) has to be monitored from a remote control center. When an autonomous vehicle encounters an unexpected driving environment, such as road construction or an obstruction, it should request assistance from a remote operator. Nevertheless, large amounts of data, including images, radar and lidar data, etc., have to be transmitted from the vehicle to the remote center. Therefore, this paper proposes a data compression method of in-vehicle networks for remote monitoring of autonomous vehicles. Firstly, the time-series data are rearranged into a multi-dimensional signal space. Upon the arrival, for controller area networks (CAN), the new data are mapped onto a time-data two-dimensional space associated with the specific CAN identity. Secondly, the data are sampled based on differential sampling. Finally, the whole set of data are encoded using existing algorithms such as Huffman, arithmetic and codebook encoding methods. To evaluate system performance, the proposed method was deployed on an in-house built autonomous vehicle. The testing results show that the amount of data can be reduced as much as 1/7 compared to the raw data.

Keywords—Autonomous vehicle, data recording, remote monitoring, controller area network.

I. INTRODUCTION

AUTONOMOUS vehicles are expected to offer many benefits, including reduced traffic and parking congestion (and therefore infrastructure savings), independent mobility for low-income people (and therefore reduced need for public transit), increased safety, energy conservation and pollution reductions. However, these advantages will only be significant when autonomous vehicles become common and affordable, probably in the 2040s to 2050s [1]. Currently, The Society of Automobile Engineers (SAE) defined six levels of autonomous driving, according to their relative extent of automation [2]. Level 0 refers to the traditional vehicle, on which the human driver take all aspects of the dynamic driving task. Level 1 refers to the vehicle with driver assistance system, which supports the driver but do not take control. Level 2 defines partly automated driving, where systems can also take control, but the driver remains responsible for operating the vehicle. Level 3 refers to highly automated driving, where the driver can disengage from the driving for extended periods of time in certain situations. Level 4 defines fully automated driving,

R. T. Juang is with the Automotive Research and Testing Center, Taiwan. (phone:886-4-7811222; fax: 886-4-7812336; e-mail: rtjuang@ artc.gov.tw)

where the vehicle drives independently most of the time, while the driver remains able to drive but can, for example, takes a nap. Level 5 defines full automation, where the vehicle assumes all driving functions and the people in the vehicle are only passengers.

To achieve full automation, many companies are working on self-driving cars. Unfortunately, some vehicles crashed recently [3], [4]. To help determine what the vehicles are doing before, during and after crashes, self-driving cars are required to equip with data recorders to collect information of driving behavior [5]. Unlike the traditional vehicles, self-driving cars utilize a combination of advanced sensors, such as stereo cameras and long- and short-range radars, and lidars, to monitor and respond to their surroundings. These sensors can generate a huge amount of data per second. Therefore, this paper proposes a method of data compression for remote monitoring of autonomous vehicles. Fig. 1 shows the system architecture of remote monitoring for self-driving cars. The proposed data recorder is deployed on the autonomous vehicle. Data on the in-vehicle network are compressed and transmitted to the remote center for the purposes of vehicle monitoring and data analysis.

The rest of this paper is organized as follows. Section II presents the system architecture and the proposed scheme. Section III shows the test results. Finally, Section IV provides some concluding remarks.
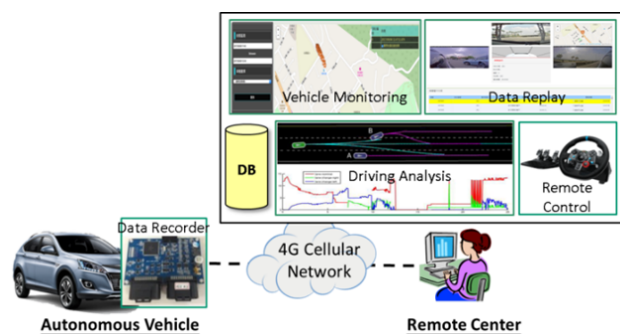

Fig. 1 Remote monitoring of autonomous vehicles

II. SYSTEM ARCHITECTURE AND PROPOSED SCHEME

Besides CAN, autonomous vehicles are usually equipped with Ethernet. Fig. 2 shows the heterogeneous architecture of the in-vehicle network, which consisted of CAN bus and Ethernet. The decision and control modules are connected with the CAN bus, while the advanced sensors are connected with the Ethernet. The CAN network and the Ethernet are connected

through a gateway, i.e., the data recorder, which collects all the data from the Ethernet and CAN network. In additional to data storing, the data recorder also transmits the collected data to a remote control center through the 4G cellular network.
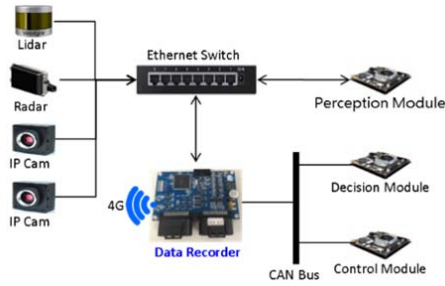

Fig. 2 Heterogeneous architecture of in-vehicle network

Fig. 3 shows the software block diagram of the proposed data recording. The input interface is either CAN bus or Ethernet. The data sources include perception module, decision module, control module, lidar, radar, cameras, RTK GPS, IMU, and odometer. The data parser tells if the message is for real-time monitoring or historical data recording. The parameters of the real-time monitoring, including vehicle location, speed, heading, mileage, diagnostic trouble code, etc., are sent to the remote center every second. Meanwhile, the historical data, including all the data on the in-vehicle network, are compressed into files with a period of ten minutes. The historical data files are sent to the remote control center when available.

As the autonomous vehicles generate large amounts of data constantly, the data have to be compressed to facilitate the transmission to the remote center. Fig. 4 shows the compression block diagram of the proposed data recording for in-vehicle networks. Fig. 5 shows the original time series of the CAN data, which is consisted of CAN identity (ID), data length code (DLC) and the data. Firstly, the time series data are grouped into a multi-dimensional signal space. Upon the arrival of a CAN message, the new data are mapped onto a time-data two-dimensional space associated with the specific CAN ID, as shown in Fig. 6. Secondly, the multi-dimensional data are sampled based on the differential sampling. Finally, the whole set of data are encoded using existing algorithms such as Huffman, arithmetic and codebook encoding methods.
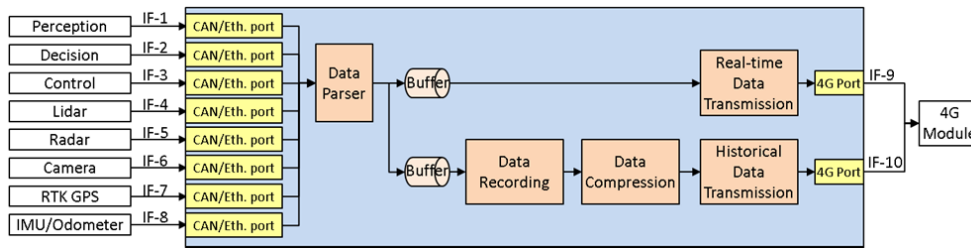

Fig. 3 Software block diagram of the proposed data recording for in-vehicle network
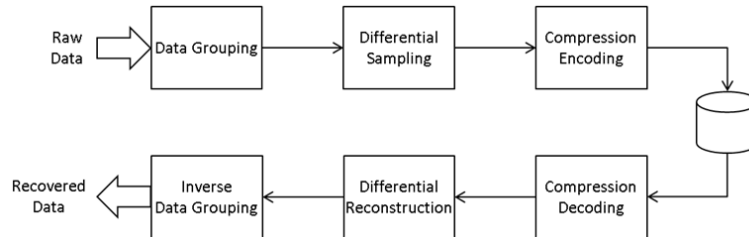

Fig. 4 Compression block diagram of the proposed data recording for in-vehicle network
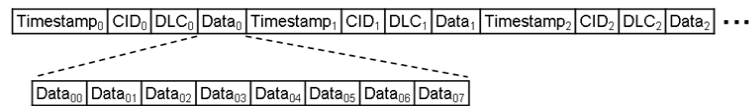

Fig. 5 Time series of CAN data

Fig. 7 shows the dataflow of the remote monitoring for autonomous vehicles in this paper. The data recorder collects vehicle's information and sends the data to the remote center through the 4G cellular network. The real-time data receiver in the figure decodes some selected parameters for vehicle monitoring, while the historical data file receiver aggregates all the data collected at the data recorder. Both the real-time data and the historical data are imported into a database. Meanwhile, a web server provides web pages for users to monitor the vehicles and download the historical data for further analysis. When the autonomous vehicle encounters an unexpected driving environment, the remote operator can send control

commands to the vehicle through the remote command transmitter shown in the figure.

III. TESTING RESULTS

The data recorder was deployed on an in-house built self-driving e-golf cart. Fig. 8 shows the e-golf cart and the associated modules, including a lidar, a camera, a HMI, three ultrasonic sensors, a GPS/IMU, a battery management system, electronic chassis modules, a wireless charging module, and a decision module. The e-golf cart provides shuttle service on the campus of ARTC (Automotive Research and Testing Center). As shown in Fig. 9, there are seven stops along the shuttle route. All the information on the heterogeneous network was collected by the data recorder on the vehicle. Then, the data were compressed and sent to a remote center through the 4G cellular network. The data were compressed as a file every ten minutes. All the modules on the e-golf cart generated more than

50 kinds of CAN messages with different periods. During each ten-minute, 150,565 records were collected. Each CAN record was consisted of arrival time, CAN ID, DLC, and data bytes. The total size of raw data during ten minutes was 2,198,467 bytes. By using the proposed compressed method, the data size was reduced to 305,000 bytes. The compression ratio reached as high as 1/7.

							CAN ID	
Timestamp	$Data_{00}$	$Data_{01}$	$Data_{02}$	$Data_{03}$	$Data_{04}$	$Data_{05}$	$Data_{06}$	$Data_{07}$
Δt_1	ΔD_{10}	ΔD_{11}	ΔD_{12}	ΔD_{13}	ΔD_{14}	ΔD_{15}	ΔD_{16}	ΔD_{17}
Δt_2	ΔD_{20}	ΔD_{21}	ΔD_{22}	ΔD_{23}	ΔD_{24}	ΔD_{25}	ΔD_{26}	ΔD_{27}
Δt_3	ΔD_{30}	ΔD_{31}	ΔD_{32}	ΔD_{33}	ΔD_{34}	ΔD_{35}	ΔD_{36}	ΔD_{37}

Fig. 6 Data grouping and differential sampling of the proposed method
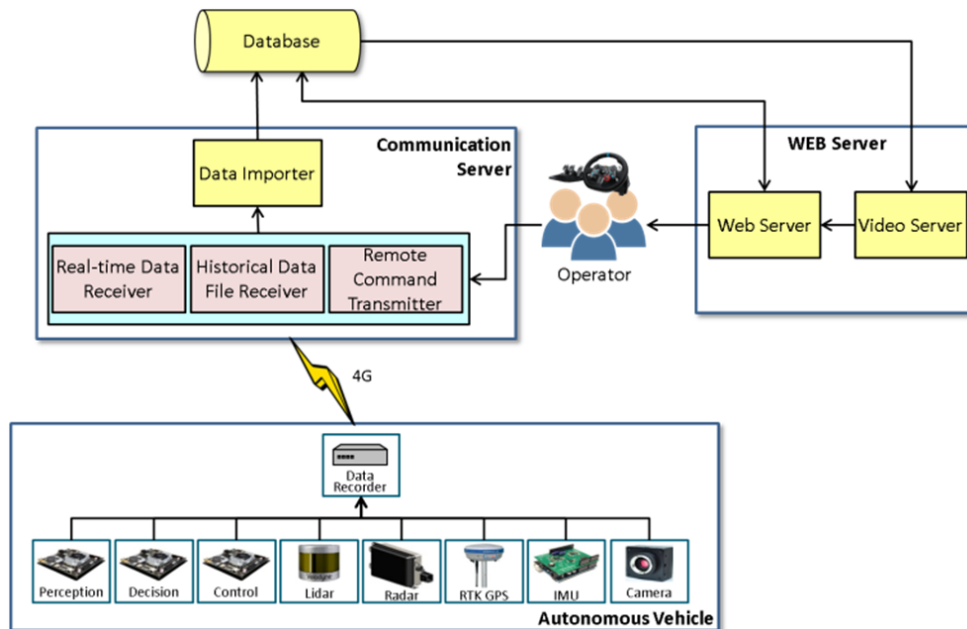

Fig. 7 Dataflow of the proposed remote monitoring for autonomous vehicles

Fig. 8 The in-house built self-driving e-golf cart

Fig. 9 Operating route of the shuttle service

IV. CONCLUSIONS

This paper has presented a data recording method for remote

monitoring of autonomous vehicles. The time series data on the in-vehicle network are grouped into a multi-dimensional signal space. Upon the arrival of a CAN message, the new data are mapped onto a time-data two-dimensional space associated with the specific CAN ID. Afterwards, the multi-dimensional data are sampled based on the differential sampling. Lastly, the whole set of data are encoded using existing algorithms such as Huffman, arithmetic and codebook encoding methods. The data recorder was deployed on an in-house built self-driving e-golf cart, which provides shuttle service on the campus of ARTC. The test results show that the data size can be reduced to 1/7 by using the proposed method.

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