IOT Based Advanced Driving Car UsingNode MCU

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***Abstract*—Autonomous driving technologies can provide greater safety, comfort and efficiency for future transportation systems. Until now, much of the research effort has been devoted to developing different sensing and control algorithms. However, there has been limited research on how to handle sensor errors efficiently. A simple error in the sensor may lead to an unexpected failure in the whole autonomous driving function. In those cases, the vehicle is then recommended to be sent back to the manufacturer for repair, which costs time and money. This paper introduces an efficient automatic on-line sensor correction method. The method includes four major functions: sensor error detection, human teaching, vehicle learning, and vehicle self-evaluation. The first function is assumed to be ready and the major contribution of this paper is the human-vehicle teaching and learning framework, which utilizes human-vehicle interaction to collaboratively adjust the parameter in the control model in order to compensate for the errors of the sensors. The self-evaluation function is also briefly introduced. The applications of this method to radar and vision sensors to recover adaptive cruise control and lane keeping functions are introduced in detail. Experimental results acquired from high-fidelity 1/10-scale autonomous driving vehicles illustrate the effectiveness and advantages of the proposed approach.**

***Index Terms*—Sensor correction, teaching-and-learning, adaptive cruise control, autonomous lane keeping**

I. INTRODUCTION

AUTONOMOUS driving technology is becoming increasingly prevalent throughout many industries. It is widely believed that autonomous vehicles can significantly reduce traffic accidents, save fuel, avoid traffic congestion and increase productivity [1],[2]. The typical architecture of autonomous vehicles consists of multiple types of sensors and on-board computers that take input from sensors and generate steering and throttle control output. Generally, the algorithms that are used to compute the control output can be categorized into two different approaches. The first is the model based control approach [1]-[6], which requires knowledge about the theoretic model of the sensor's perception process and vehicle's dynamics. The other approach is the neural network based approach [7]-[10], which utilizes a neural network (NN) to generate control output directly. This approach does not require the designers to clearly understand the mathematical model of each part of the system, but it needs a laborious training data collection process and excessive computing capacity to train theNN effectively [11]-[14].

Any type of autonomous driving controller requires accurate sensory information as its input. To meet the requirements, sensors need to go through a complex offline calibration process in order to transfer the raw data in the sensor frame to meaningful data in the vehicle frame. Although the main purpose of autonomous vehicles is to safely drive without human intervention, some unexpected accidents may still occur which causes the sensors to lose their standard configuration. Existing autonomous driving controllers cannot recover the calibration and the autonomous driving functions will be compromised. The vehicle then needs to be sent back to the manufacturer for repair, costing both time and money. Many methods have been proposed to solve such problems, but most of them are subject to major limitations. Some of them need a special feature to do the correction [15]-[16], and the correspondence between sensor data and the feature needs to be found either manually or semi-automatically [17]-[19]. For certain types of sensors, dedicated moving paths are needed [20]-[23]. Some researchers have proposed fully-automatic online sensor error correction methods [24]-[28], but they can only correct misalignment between sensors, none can correct the errors between the sensors frame and the world frame. Nvidia has proposed a framework that uses a deep learning neural network to teach an autonomous vehicle how to drive [29]. However, this approach can only learn the driving scenarios that the human driver has demonstrated, thus exhaustive human driving data would be required to cover all possible driving scenarios, which is inefficient in terms of both cost and time.

The major contributions of this paper are to develop a human-vehicle teaching-and-learning framework that utilizes model based autonomous driving controller and non-linear optimization algorithm to handle sensor parameter errors in autonomous vehicles. The model-based autonomous driving controller will correct the sensor error by learning from human expert demonstrations. In the remaining section of this paper, an automatic on-line sensor error correction framework is proposed and the human teaching, vehicle learning, and vehicle self-evaluation are then introduced. The vision system errors in autonomous lane keeping system and radar errors in adaptive cruise control system are adopted as examples to illustrate the design and implementation of the framework. The implementations are verified on a 1/10 scale (every dimension of the vehicle is about a tenth of a real vehicle) high-fidelity experimental autonomous vehicle. Experimental results show that the proposed approach does not require a large set of training data and the learning process is very efficient. Therefore, the proposed framework can increase the flexibility of autonomous vehicles and reduce the maintenance cost of autonomous vehicles when unexpected accidents occur on their sensing systems.speed, position, steering angles and surrounding information such as the images with lanes and forward vehicle distances.

While a human driver can have improper driving behaviors in reality, we assume that in this paper the human driver is always performing well enough to teach the autonomous controller, and leave the human driver performance evaluation problem for future research.

C. Vehicle Learning

II. Automatic Sensor Correction

A. General Process

The general process of automatic sensor correction can be described as Fig. 1. The whole process can be divided into 3 functions: sensor error detection and notification, human-vehicle teaching-and-learning, and vehicle self-evaluation. Among these processes, the sensor error detection and classification problem has been studied extensively [30]-[42]. In this paper, we assume that this function is already available and will not be discussed in detail. The human teaching, vehicle

During autonomous driving, motion planner generates the desired motions based on the given task and real-time sensory information and the motion controller executes the generated motions through a feedback controller using the real-time sensory feedback. The key mission of the vehicle learning process is to synthesize or adapt the motion planner and motion controller based on the sensory information from the human driver's demonstrations. In this paper, we are dealing with the adaptation problem, where the autonomous vehicle has an existing motion planner and motion controller for the given tasks, and the parameters in the control model will be updated in the presence of sensor errors. In the remainder of this section, the method we used to update the parameters in the controller is described in detail.

Human Teaching Process

Vehicle Learning Process

vehicles. Sensors mounted on the vehicle will record the human-driven vehicle's information such as the vehicle's learning and vehicle self-evaluation process will be introduced in the following sections.

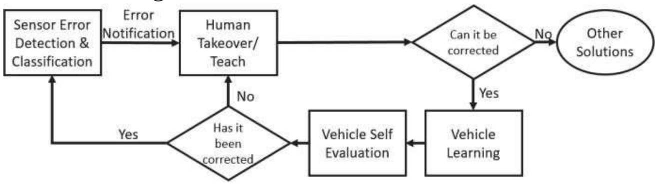
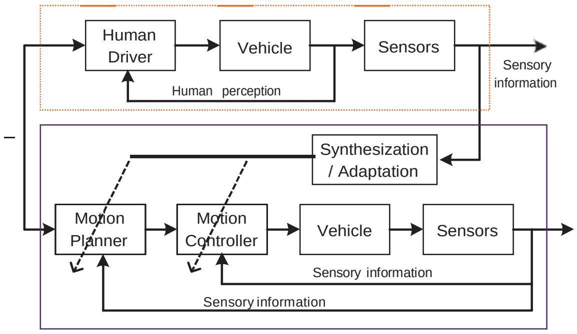


Fig. 1. General process of automatic sensor correction

B. *Human Teaching*

The relationship between human teaching and vehicle learning process is shown in Fig. 2. In the human teaching process, given a driving task such as lane tracking or adaptive cruise control, the human driver acts as a perception system, a motion planner and a motion controller to execute it. The perception and command data collected during human driving process will serve as an expert demonstration for autonomous



in this paper, we assume the road ahead is ideally flat to estimate the lane markers' 3D coordinates in the vehicle frame from the 2D coordinates captured by a camera. M_{unit} is a unit transformation matrix which transfers the values of the coordinates from standard units to the units used by the sensor.
M_{unit} and M_{proj} represent the intrinsic parameters of the sensor, which are not affected by sensor extrinsic errors.
M_{trans} represents the extrinsic parameters of the sensor, which are vulnerable to errors. In reality, this matrix will contain six variables: three rotation angles a, β, y and three translation distances X_0, Y_0, Z_0[47].

Once the relationship between coordinate p and P is derived, given coordinate p in sensor frame based on equation (1), it is possible to find the coordinate P in the vehicle frame. Furthermore, the measurement indices based on P can be calculated for the given task. For example, once the coordinates of lane markers in the vehicle frame are estimated, the measurement index for lane keeping task, the steering command output, can be calculated.

Therefore, we denote the measurement indices for a given task as $M = [m_1, m_2, \ldots, m_n]^T$, where m_i means a specific measurement index. Next, we define all parameters in equation (1) as θ, then the measurement indices can be expressed by equation (2):

$$m_k = f_k(p, \theta) \quad (2)$$

When sensing exceptions occur, the major mission is to find the new parameters $\hat{\theta}$ to recover the autonomous driving function. In the human teaching process, a human driver manually drives the vehicle to perform the given task. During the human driving, sensory data p in the sensor frame is directly recorded. Under the assumption that the human driver is driving well, it is reasonable to consider the measurement indices calculated based on p as the desired measurement indices
$M^d = [m_1^d, m_2^d, \ldots, m_n^d]^T$. Therefore, the desired measurement indices can be expressed by equation (3):

$$m_k^d = f_k(p, \hat{\theta}) \quad (3)$$

Since p and $M^d = [m_1^d, m_2^d, \ldots, m_n^d]^T$ are all known, $\hat{\theta}$ can be found by solving equation (3). If the functions $f_1, f_2, \ldots, f_n$ are all linear functions, the least square method can be adopted to find $\theta^\wedge$. For many sensor applications in autonomous vehicles, these functions are not linear. Therefore, non-linear based optimization methods such as Gauss–Newton method [48], Levenberg–Marquardt method [49], trust region reflective method [50] and pattern search [51] method can be adopted to find $\hat{\theta}$ based on the complexity of these functions and the availability of data from the human teaching process.

D. Vehicle Self-Evaluation

The vehicle self-evaluation process needs to verify the learning effectiveness and terminate the teaching-and-learning process when the learning result is good enough. The structure of the vehicle self-evaluation process is shown in Fig. 3. any set of learned parameters.

One important feature that can be learned from the

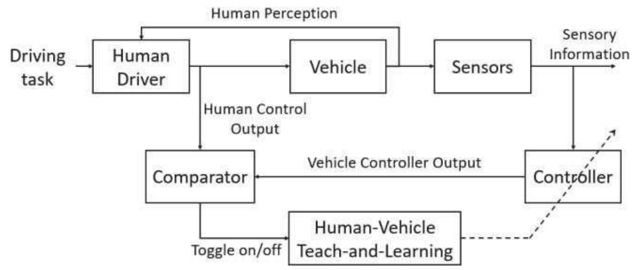


Fig. 3. Vehicle self-evaluation

When an autonomous driving controller has learned the sensor error from the driver properly, the control output from the controller should be similar to the control output from the human driver. We divide the data collected during human teaching into "batches". After the controller has learned from one or several data batches, the next incoming batch is used as the validation data set. If the calculated residual indices, represented by E_y, between the controller's output y_c and the human driver's output y_h over the validation set is within a predefined tolerance value E_{max} , then the controller can be considered as having a good performance over this batch. If the controller successfully performs well over multiple batches that can cover different driving scenarios, then the controller can be considered as properly trained and the teaching-and-learning process can be terminated. However, if the controller fails to pass this evaluation process, it will need to learn from more batches until the error E_y is smaller than E_{max}.

Specifically, when this self-evaluation process is applied together with optimization methods, the detailed process can be described as Fig. 4. In an optimization algorithm, the undetermined parameters need to be initialized with initial values first and then updated with new values that bring the value of cost function E_y to a local minimum over the training data batch. If the new parameters cannot keep the cost function's value small enough over a validation data set, the optimization process will start over again with the previously optimized parameters as the initial parameters. The optimization process will be repeated until target cost value is met.

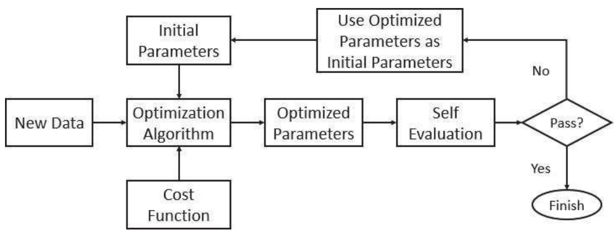


Fig. 4. Self-evaluation applied to optimization algorithms

III. APPLICATION OF VISION SENSOR ERROR HANDLING IN AUTONOMOUS DRIVING

In this section, the application of the proposed automatic sensor correction algorithm to handle camera errors in autonomous driving is described in detail.
experiments with error scenarios 1 and 2 is the threshold that distinguishes the "acceptable" training result from the "unacceptable" result. Combining TABLE I. and TABLE II.

VI. CONCLUSION

A human-vehicle teaching-and-learning framework is developed and applied to handling vision sensor errors and distance sensor errors in autonomous vehicles. The human teaching and vehicle learning processes and self-evaluation scheme are introduced in this paper. Experimental results on 1/10 scale autonomous vehicles and simulator demonstrate that the proposed method can handle the exceptions very quickly with a brief demonstration. It was shown that a large dataset was not needed for the human teaching and vehicle learning. Although with the limited amount of data collected during a short period of time the autonomous controller's performance may not be fully restored to OEM standard, the basic autonomous driving function should be able to be recovered and the vehicle can continue to serve the user. More data during human driving in the future can be collected so that the controller can be improved and eventually reach the required safety standard. Therefore, our method can increase the flexibility and reduce the maintenance cost of autonomous vehicles when unexpected events occur on their sensing systems.

The scalability of the proposed method can be foreseen in many applications in other types of sensors or faults. There are a variety of different failure modes for different sensors, and the algorithm we proposed can be applied to those that satisfy the following requirements:

(1) The sensor is having a failure due to errors in calibration. The sensor itself is still functional.
(2) The relationship between the sensor readings and the corresponding physical information in the world framecan be analytically modelled.
(3) A clear and consistent measurement can be found for the measurement indices from the environment during daily driving for re-training purpose.

Sensor failures that can be solved by our algorithm include the misalignment of cameras, LIDARs, radars and IMUs, as well as the calibration software malfunctions of these sensors. The structural damage to these sensors, or some other sensors that do not respond to any obvious references in the

sensor and more consistent values of such measurements while human is driving the vehicle. It is also possible to environment, for example GPS sensors, cannot be handled by our proposed approach.

When a correctable sensor is used in multiple functions, our propose approach is still applicable by utilizing the training data from the function which can provide more measurements related to the leverage different functions to formulate the problem as a multi-objective optimization problem, which may be able to further improve the correction results than using just one function. All these mentioned examples indicate the future extensions and applications of this research work.

RC Radio Controlled
ACC Adaptive Cruise Control LIDAR Light Detection and Ranging
RADAR Radio Detection and Ranging IMU Inertial Measurement Unit
GPS global positioning system
2D Two-Dimensional
3D Three-Dimensional
PID Proportional–Integral–Derivative
WiFi Wireless Fidelity
USB Universal Serial Bus MSE Mean Squared Error
OEM Original Equipment Manufacturer

APPENDIX

Acronyms List

NN Neural Network

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