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An Integrated Manual and Autonomous Driving Framework based on Driver Drowsiness Detection

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Abstract— **In this paper, we propose and develop a framework for automatic switching of manual driving and autonomous driving based on driver drowsiness detection. We first present the scale-down intelligent transportation system (ITS) testbed. This testbed has four main parts: an arena; an indoor localization system; automated radio controlled (RC) cars; and roadside monitoring facilities. Second, we present the drowsiness detection algorithm which integrates facial expression and racing wheel motion to recognize driver drowsiness. Third, a manual and autonomous driving switching mechanism is developed, which is triggered by the detection of drowsiness. Finally, experiments were performed on the ITS testbed to demonstrate the effectiveness of the proposed framework.**

I. INTRODUCTION

A. Motivation

With nearly 43,000 deaths a year on U.S. roads [1], [2] and increasing traffic delays in major metropolitan areas, a need exists for countermeasures to reduce the number and severity of traffic accidents, as well as relieve traffic jams. Intelligent Transportation Systems (ITS) has attracted more and more attention in recent years due to their great potential in meeting this need [3], [4], [5]. As a rigorous part of the ITS research, autonomous vehicles such as Google's self-driving car [6] has been developed recently.

Though fully autonomous driving appears promising for future transportation systems, mass deployment of driverless cars may still be decades away. There are many hurdles to the wide adoption of fully autonomous driving, including reliability to liability issues. In this paper we argue that integrated manual driving and autonomous driving may be more practical for real world deployment. A vehicle can be equipped with autonomous driving capability but it will only drive by itself in certain special conditions for a short period of time. For example, when the driver is getting drowsy, or in some urgent situations when the driver loses control of the car. In this paper, we aim to validate such integrated driving by considering the case that the driver is drowsy. Our experiments will be conducted on a small-scale ITS testbed developed in our lab.

The rest of this paper is organized as follows. In the remainder of this section, we present the related work. In Section II we give an introduction to the ITS testbed developed in our lab, including both hardware and software platforms. Section III describes the drowsiness detection algorithm. Section IV details the mechanism for manual/autonomous driving switching. Experiment evaluation is explained in Section V and Section VI concludes this paper and discusses some future research directions.

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B. Related work

Autonomous driving has been researched for a long time. In the 1980s a vision-guided Mercedes-Benz robotic van, designed by Ernst Dickmanns and his team at the Bundeswehr University Munich in Munich, Germany, achieved 100 km/h (62 mph) on streets without traffic [7]. Also in the 1980s the DARPA-funded Autonomous Land Vehicle (ALV) achieved the first road-following demonstration that used laser radar and computer vision to control a robotic vehicle up to 30 km/h [7]. The PATH (Partners for Advanced Transportation Technology) project conducted in California [8], [9] is one of the earliest to demonstrate the platooning of a fleet of self-driving cars. Following the successful DARPA Grand Challenge, autonomous driving has been attracting growing interest in recent years [10].

However, the real world mass deployment of such autonomous cars is still far away. First, the reliability and robustness of the autonomous cars should be greatly improved before they can be really used in various weather, lighting, and road conditions. Current technologies still fall far short of autonomous driving in extreme conditions. Second, legal issues concerning the liability when such autonomous cars are involved in accidents have not been sorted out, which may make the automotive industry reluctant to manufacturing driverless cars, even when the cars are reliable and robust. Therefore, research efforts have been devoted to the use of autonomous cars in applications where safety is not a major concern, such as on golf courses.

We believe that intermittent autonomous driving during human driving when special conditions occur can be a good application, for example, when the driver temporarily loses the control of the car, such as getting drowsy. In recent years, the development of robust and practical drowsiness detection system has been gaining attention. Many of the world's major motor companies like Toyota, Ford, Mercedes-Benz and others are currently employing car safety technologies which prevent accidents from happening when the driver is getting drowsy. However, their approach is to wake up the driver after drowsiness is detected, which may not be effective in avoiding accidents if the driver reacts too late.

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Fig. 1. The overall ITS testbed.

Real time drowsiness detection has been implemented through different detection techniques analyzing different types of input data. The first approach is analyzing the car controller information such as steering wheel and gas pedals to detect the drowsiness of the driver [11], [12]. The second set of techniques makes use of the measurement of variations in the physiological activities of the human body such as brain wave (EEG), heart rate or pulse rate [13], [14], [15]. Even though the measurements and their correlation with the alertness of the driver is quite accurate, they are not practical as it would require the driver to always wear the sensing devices and the hardware cost is too high to be used for commercial purposes. The third approach is making use of computer vision and image processing applications to detect the drowsiness of the driver through the changes in his/her facial expressions [16].

With the ultimate goal being finding a practical and unobtrusive method of detecting drowsiness of a driver, using the steering wheel data analysis or the computer vision approach alone may not be sufficient to determine the state of the driver under different circumstances and different behavioral manifestations of the driver. For example, the nature of the road or the way the driver drives will highly affect the decision making process when using the steering wheel data analysis. Similarly the presence of sufficient light and the way the driver behaves when he/she is drowsy will influence the detection accuracy when using the computer vision approach. Therefore integrating the two approaches will certainly increase the detection reliability and encompass situations where only one approach may not give sufficient results. Hence, we implemented the steering wheel data analysis approach and the computer vision approach, which are then integrated to give a final decision on the state of the driver.

II. Intelligent Transportation System Testbed

To verify our proposed idea, we will conduct experiments on a scale-down testbed, which is useful for preliminary study and feasibility test. This approach strikes a balance between real-size vehicles and pure computer simulations. Our small scale testbed can simulate real traffic environments, autonomous driving, vehicle communication, as well as human driving experience.

A. Hardware Setup of the Testbed

The overall testbed is shown in Figure 1. The scale-down ITS testbed we developed has four main parts:1) an arena, 2) an indoor localization system, 3) automated radio controlled (RC) cars and 4) roadside monitoring facilities, which are described below:

1) Arena: The arena is built based on a wooden floor on which streets, roads and intersections can be set up. It has a dimension of 16 feet by 12 feet. A carpet on top of the wooden floor is used to mimic concrete or asphalt road surfaces.

2) Indoor localization system: An indoor localization system is built up to localize RC cars in the simulated traffic environment. The purpose of this system is to provide location feedback of the cars to support autonomous driving. This indoor localization system can mimic the function of the GPS system in the real world. It is developed from an optical motion capture system (OptiTrack) from NaturalPoint, Inc [17]. There are 12 cameras to cover the whole arena. The OptiTrack system is capable of capturing 100 frames per second, therefore the location and orientation information can be obtained in real time and with high accuracy. The OptiTrack system tracks each RC car via the markers mounted on top of the RC car.

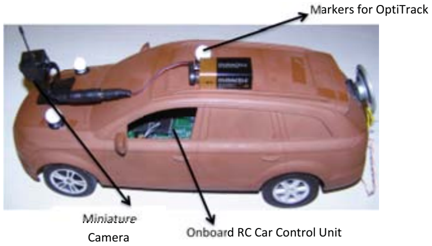

Fig. 2. The automated RC car for both manual and autonomous driving.

3) Automated RC cars: We used commercial off-the-shelf RC cars with a scale of 1:14 to develop the automated RC car. There are two major parts in the hardware design: a control board embedded in the RC car body and an XBee wireless module. An embedded control board is developed to replace the original circuit board inside the RC car. The PWM output from the control board is used to drive the front servo motor and the rear DC motor so that the orientation and the velocity of the RC car can be controlled, respectively. The XBee wireless module has a data rate up to 250Kbps and can serve as the communication channel between RC cars, as well as between RC cars and roadside infrastructures.

The automated RC car has both autonomous driving and human driving capability. For autonomous driving, four markers are mounted on top of the automated RC car to build a rigid body so that the location and orientation of the car can be tracked. The tracking control algorithm that allows the RC car to track predefined trajectories is developed in the computer, and the control commands are sent to the RC car via the Xbee wireless communication. For manual driving, a miniature wireless camera is mounted on the hood of the RC car to provide visual inputs, as shown in Figure 2. It is used to observe the environment in front of the car and send the video stream through wireless communication to the PC. The human driver sits in front of a racing wheel stand (a Logitech G27) and drives the RC car while he/she observes the video stream on the monitor. We developed a program using the software development kit (SDK) of the wheel stand to read the data from the racing wheel which include the wheel turning angle, brake, gas pedal and gear shift status. Based on that, we send control commands, such as "move forward", "backward", "turn left", "turn right", "speed up", or "slow down", through the Xbee wireless communication to the automated RC car. The whole setup of this human driving system is shown in Figure 3.

4) Roadside monitoring facilities: A Mobotix Q24 fisheye camera as shown in Figure 1 is mounted over the arena to serve as a roadside monitoring facility. This camera is capable of providing different views simultaneously, including a full 360 degree all-round view, hence it can cover the whole arena to monitor the traffic underneath it. This camera uses an IP-based interface. The stream of live images from the camera is obtained through a socket connection. The features of the camera (including resolutions, frame rates, etc) can be easily modified by sending a web request. The camera provides a highest resolution of 3M pixels and the color images are scalable from 160×120 to 2048×1536. This camera can be used in research projects involving traffic monitoring, such as automated collision detection or anomaly detection through visual surveillance.

Fig. 3. The setup for manual driving.

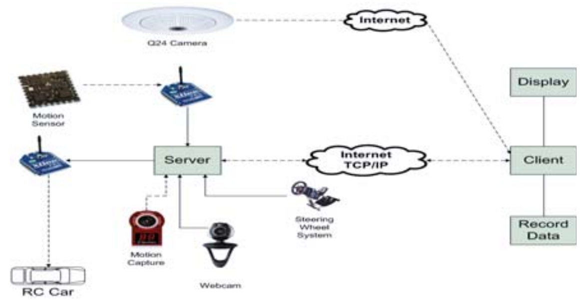

Fig. 4. The data collection setup.

B. Data collection setup

To make our ITS testbed accessible to users, both local and remote, we developed a data server to stream all the sensor data to clients. Therefore, as long as the client has access to the Internet, it can connect to the server and request for the data it needs. This will enable cloud-based computing and process on the collected data.

The overall data collection setup is illustrated in the Figure 4. The dashed lines represent the wireless communication. The solid lines represent the wired communication via USB or Ethernet cables. The server can stream the sensor data from the racing wheel, the indoor localization system and an IMU motion sensor on the RC car which can obtain the raw 3D acceleration, angular rate and the roll, pitch, yaw data of the car. Additionally, we also streamed video from the webcam that monitors the driver's face and the overhead fisheye camera that monitors the whole testbed. All the data are synchronized at a sampling frequency of 20HZ.

III. Driver Drowsiness Detection

Drowsiness is one of the main causes of severe traffic accidents. In our implementation, we used two channels of information: images of the driver's face and steering wheel data. Previous works have mainly focused on developing a drowsiness detection method using only one channel of information, but we employed both of them, preprocessed them and integrated them at feature level to obtain reliable drowsiness decisions. The drowsiness detection algorithms are implemented as a remote client application where the two sets of inputs transmitted from the server are processed and the final decision is sent back to the server.

As can be seen from the system diagram in Figure 5, there are three main components of the system: facial expression feature extraction, steering wheel feature extraction and feature level integration.

A. Facial Expression Feature Extraction

Using facial expressions to determine the drowsiness condition involves the following steps: accepting the stream of images in real time from the data server through the TCP/IP network, detecting the face of the driver from the image frame, processing the image to determine the state of the driver.

The system accepts a stream of images from the server at a rate of 20 frames per second. When a frame is captured, we first convert it to grayscale and use histogram equalization to facilitate face detection. We have used the Viola-Jones robust real time face detection algorithm [18] implemented in OpenCV [19] to detect the driver's face. Once the face is detected, features are extracted. To do that, two different areas of interest are used: the face area and the eye region. The area of interest is fed to Gabor wavelet decomposition of 2 scales and 4 orientations to extract the facial features. To reduce the number of features, we employed Adaboost weak learning algorithm [20] to select the most important features for classification. The weak classifiers are based on a single facial feature and the features with the minimum classification error are selected. For the weak classifiers, two different thresholds are used: 1) Averaging: We take the average of the values of the facial feature of all training images. 2) Searching maximum: We use each value of the facial feature of all training images as a threshold of the weak classifier and choose the one that gives the maximum separation between the drowsy and non-drowsy training images.

B. Steering Wheel Feature Extraction

According to previous researches in drowsiness detection, it has been shown that there is a good correlation between the steering wheel movement and the drop in the state of vigilance while driving [11], [12]. In an alert state, the driver tends to make small adjustments to the steering wheel angle and hence there will only be small variations in the steering wheel angle. Whereas when the driver is in a drowsy state, the way he/she drives becomes unpredictable resulting in a large change in trajectory (zigzag driving) and there will be a larger amplitude of movement to keep the vehicle in the center of the lane. As shown in Figure 5, the system accepts racing wheel data from the data server at a rate of 20 packets per second. The features are extracted out of a fixed length of steering wheel data.

C. Feature Level Integration

To attain a more reliable drowsiness detection system, integrating the two independent sources of information helps improve the accuracy. After obtaining the selected facial features and the steering wheel features, we concatenate the two vectors to form a single feature vector. We feed the feature vector to an SVM classifier with Gaussian Radial Basis Function (RBF) kernel which provides a nonlinear decision hyper-plane between drowsy and non-drowsy feature vectors. During the training, we save the stream of images with detected face, the face locations, the steering wheel data vectors and their corresponding labels and train the classifier offline. During the real time testing, the final decision from the classifier is sent back to the server application to trigger the corresponding action.

IV. Switching between manual and autonomous driving

Here we describe the mechanism that enables the switching from manual driving to autonomous driving, if a drowsiness state is detected by the client program. We first give the details of the techniques for manual and autonomous driving, respectively, then we explain the switching mechanism.

A. Manual driving

During manual driving, the RC car was controlled by the Logitech G27 controller set which includes a steering wheel, gas, brake, transmission pedal and gear stick. This controller set interfaces with the computer via a USB port. Once the computer received signal from the controller, a corresponding command is sent wirelessly to the RC car via the Xbee transceiver. The command frequency is set at 20Hz. The data set of the controller includes: steering wheel; brake; gas and gear.

B. Autonomous driving

The control algorithm for autonomous driving in this project was developed in our previous work [21] which uses a virtual car-based approach to control the automated RC cars. In this project the RC car will follow a figure eight trajectory. We defined the virtual car's trajectory following the street geometry and traffic rules. To do so, we defined twelve segments. Each segment specifies the virtual car's location: $x_d = p(s)$ and $y_d = q(s)$. When the RC car reaches one segment, the virtual car in this segment would start moving and guide the RC Car to track along the designed trajectory. When the virtual car reaches the end of a segment, it waits until the RC car reaches the end of that segment and then the virtual car starts moving into next segment and repeats this process.

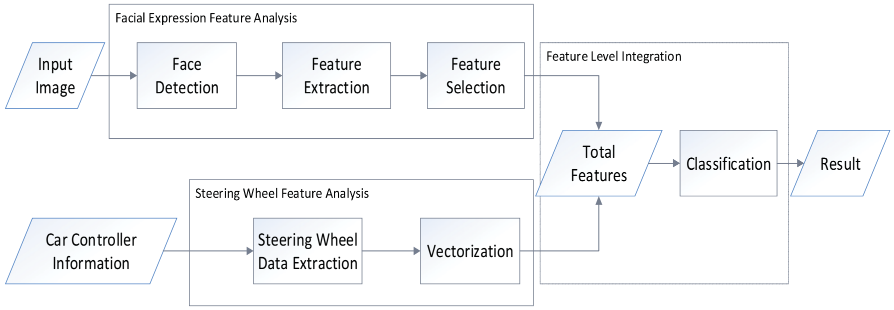

Fig. 5. The overall system diagram of drowsiness detection.

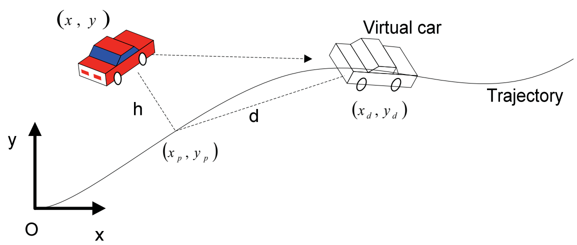

Fig. 6. Determining the virtual car starting location for the switching from manual to autonomous driving.

C. Switching between manual and autonomous driving

The driver's status is constantly monitored by the client program which sends to the server a Boolean variable to let the server determine the suitable control of the RC car based on the driver's status. When the driver is awake, the server can let him manually control the RC car via the Logitech racing wheel. When the driver gets drowsy, the server would take control of the RC car by tracking a predefined trajectory which follows the street. Before the switch, the RC car might go off the trajectory. We have to find the point (x_p, y_p) that has the shortest distance h from the RC car's current location to the predefined trajectory. Then we add the offset distance d to find the starting location (x_d, y_d) for the virtual car. The virtual car's starting location is illustrated in Figure 6. Then we use the control algorithm developed in our previous work [21] to autonomously drive the RC car.

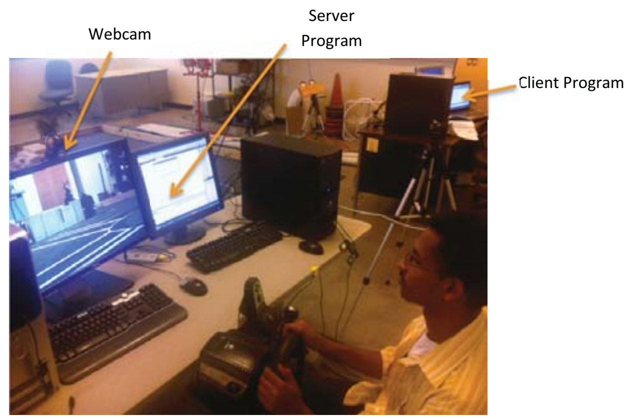

Fig. 7. Manual/autonomous switching experimental setup.

Fig. 8. The driver gets drowsy during the driving. Left: awake; Right: drowsy.

V. Experimental Validation

We conducted scale-down experiments to validate the proposed manual/autonomous driving framework. The experimental setup is shown in Figure 7. The webcam is mounted on the monitor to watch the driver's face. By integrating the facial expression and steering wheel data, the client program determines if the driver is awake (Figure 8 (left)) or drowsy (Figure 8 (right)). The drowsiness detection runs on the client computer and the results are sent back to the server to trigger the switching from manual driving to autonomous driving. At the beginning we set the control to be manual driving. Once a "drowsy" state is detected, the server switches to autonomous driving along the predefined trajectory. When the driver is awake again and the "non-drowsy" state is detected, the server let the driver gain the control again. It is worth noting that at the time of experiments, we let the driver mimic drowsiness instead of making the driver really sleepy.

The racing wheel data are plotted in Figure 9, which capture the moment of the switching. We can observe that the steering and gas values vary at the beginning. This means that the driver was controlling the RC car manually. After 300 samples (15 seconds), the steering data stays unchanged since the driver got drowsy. Then, the RC car is controlled autonomously by the server to track the predefined trajectory. After 400 samples (20 seconds), the steering and gas data changed again which means the driver is detected to be non-

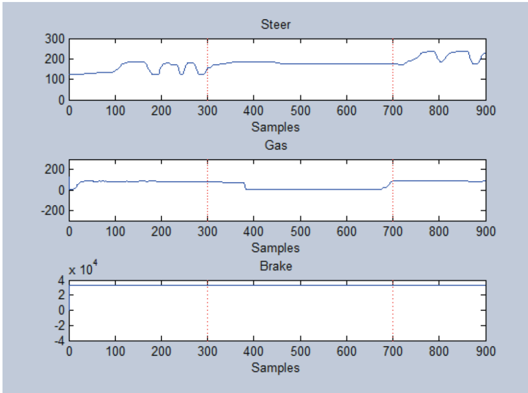

Fig. 9. The racing wheel data. The 1st red dotted lines indicate the moment of switching from manual to autonomous driving. The 2nd red dotted lines indicate the moment of switching from autonomous to manual driving.

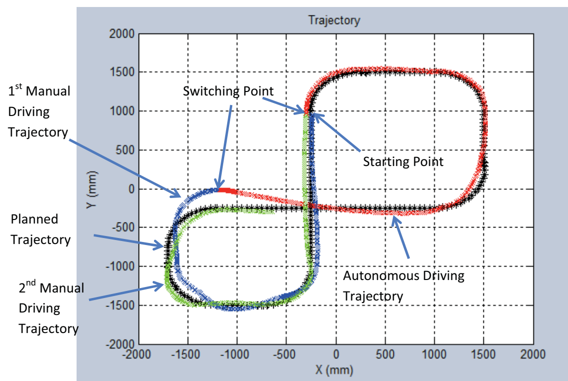

Fig. 10. The trajectory of the car.

drowsy then he can manually control the RC car. During the experiment, the brake pedal was not pressed, so its value remained unchanged.

Figure 10 illustrates the trajectory the RC car traveled by manual driving (blue curve and green curve) and autonomous driving (red curve). The black curve represents the planned trajectory. The RC car was first placed at the point (-250, 1000) and manually controlled by the driver to run downward along the blue curve. The end of the blue curve indicates the point when the driver got drowsy and this is also the point where the server autonomously controlled the RC car and started the red curve. The end of the red curve indicates the point when the driver woke up and manually controlled the RC car to run along the green curve. The recovering time depends on the distance from the RC car to the predefined trajectory. In this experiment, we noticed that the recovering time is around 4 seconds.

VI. Conclusions and Future Work

This paper proposes an integrated driving framework which can switch the car from manual driving to autonomous driving when the driver gets drowsy. This framework demonstrates that intermittent autonomous driving can be adopted as a mechanism to prevent accidents in certain abnormal situations. We conducted a scale-down experiment to evaluate the proposed framework using a small scale ITS research platform developed in our lab. In the future we will investigate how to use the motion sensor data of the car to detect abnormal driving behaviors and trigger the switching between manual and autonomous driving.

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