SOVCAN: Safety-Oriented Vehicular Controller Area Network

Yin Zhang, Min Chen, Nadra Guizani, Di Wu, and Victor C. M. Leung

The authors propose an SDN-based approach to develop the safety-oriented vehicular controller area network, which can guarantee traffic safety based on driver fatigue detection and emotion recognition, which are monitored through the driver's physiological and psychological state.

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Abstract

To meet the demands of vehicular networks, such as high throughput, high mobility, low latency, heterogeneity, and scalability, SDN has been applied for raising the user experience through providing high-performance communications between vehicular network nodes, reconstructing the vehicular network structure, and optimizing networking coverage, system security, communication latency, and so on. However, the existing SDN applications in the vehicular network mainly focus on the data communications between the vehicles and other network nodes or devices, while the vehicular controller area network is still limited to some particular applications, only providing users with basic services, but unable to meet the demands in a complex driving environment. Thus, this article proposes an SDN-based approach to develop the safety-oriented vehicular controller area network, which can guarantee traffic safety based on driver fatigue detection and emotional recognition, which are monitored through the driver's physiological and psychological state.

Introduction

With the development of mobile networks, the Internet of Things (IoT), and wireless sensor networks (WSNs), vehicular networks have gradually become one of the most effective approaches to implement intelligent transportation systems (ITS). For example, IEEE 802.11p is the standard that supports ITS applications in vehicular ad hoc networks (VANETs) [1]. Vehicle networks are expected to analyze and utilize various information inside and outside vehicles themselves through information and wireless communication techniques. Specifically, through vehicle-to-vehicle (V2V), infrastructure-to-vehicle, and vehicle-to-infrastructure (V2I) communications, which are the foundation and key support technologies determining the overall performance of vehicular networks, road safety and traffic efficiency are significantly improved.

However, the traditional wireless communication technologies are not available to meet the advanced demands from vehicular networks, including high throughput, high mobility, low latency, heterogeneity, scalability, and so on. To address the great challenge, software defined networking (SDN) has been applied to vehicular networks to improve the user experience through providing high-performance communications between the vehicular network nodes, reconstructing the vehicular network structure, and optimizing the networking coverage, system security, communication latency, and so on [2]. It can be expected that in future network configuration, various terminals, such as vehicles, will be added to the network. The traditional network structure is not conducive to managing and controlling a large number of network nodes, so they should be part of the control functions that are distributed to the edge of the network, especially in the Internet of Things (IoT) [3]. In particular, the technology of distributed computing can be used in the scenario of vehicle communication in IEEE 802.11p to improve the service quality of vehicular networks. In [4], Liu *et al.* investigate the scheduling for cooperative data dissemination in a hybrid I2V and V2V communication environment. Specifically, an approach based on a centralized scheduler at the roadside unit (RSU) is proposed to represent the first known VANET implementation of the SDN concept.

However, the existing SDN applications in the vehicular network place more attention on V2V, V2I, and even in-vehicle power line communication for data transmission [5–7], while the controller area network (CAN) is still limited to some particular applications, such as, entertainment, navigation, and location-based services, which only provide users with basic services but cannot meet the demands in a complex driving environment. Especially for driver safety, V2V and V2I can provide drivers with vehicular information to reduce the frequency of traffic accidents. For example, safety distance reminders, safety speed alerts, pedestrian reminder, collision avoidance reminders, traffic guidance, and other services can be provided. However, the current CAN cannot easily monitor drivers' physiological and psychological states to avoid traffic accidents due to drivers' fatigue and moods. Therefore, this article proposes an SDN-based approach to develop a safety-oriented vehicular CAN (SOVCAN), which can guarantee traffic safety from the following two aspects.

Drivers' Fatigue Detection: According to statistics, fatigue can significantly reduce a driver's vigilance and increase reaction time, which is an important cause of traffic accidents. Through a camera detecting the state of a driver's eyelids and the frequency of a driver's slight nodding. the system can effectively find the micro sleep behavior, and then alert and warn the driver to prevent traffic accidents.

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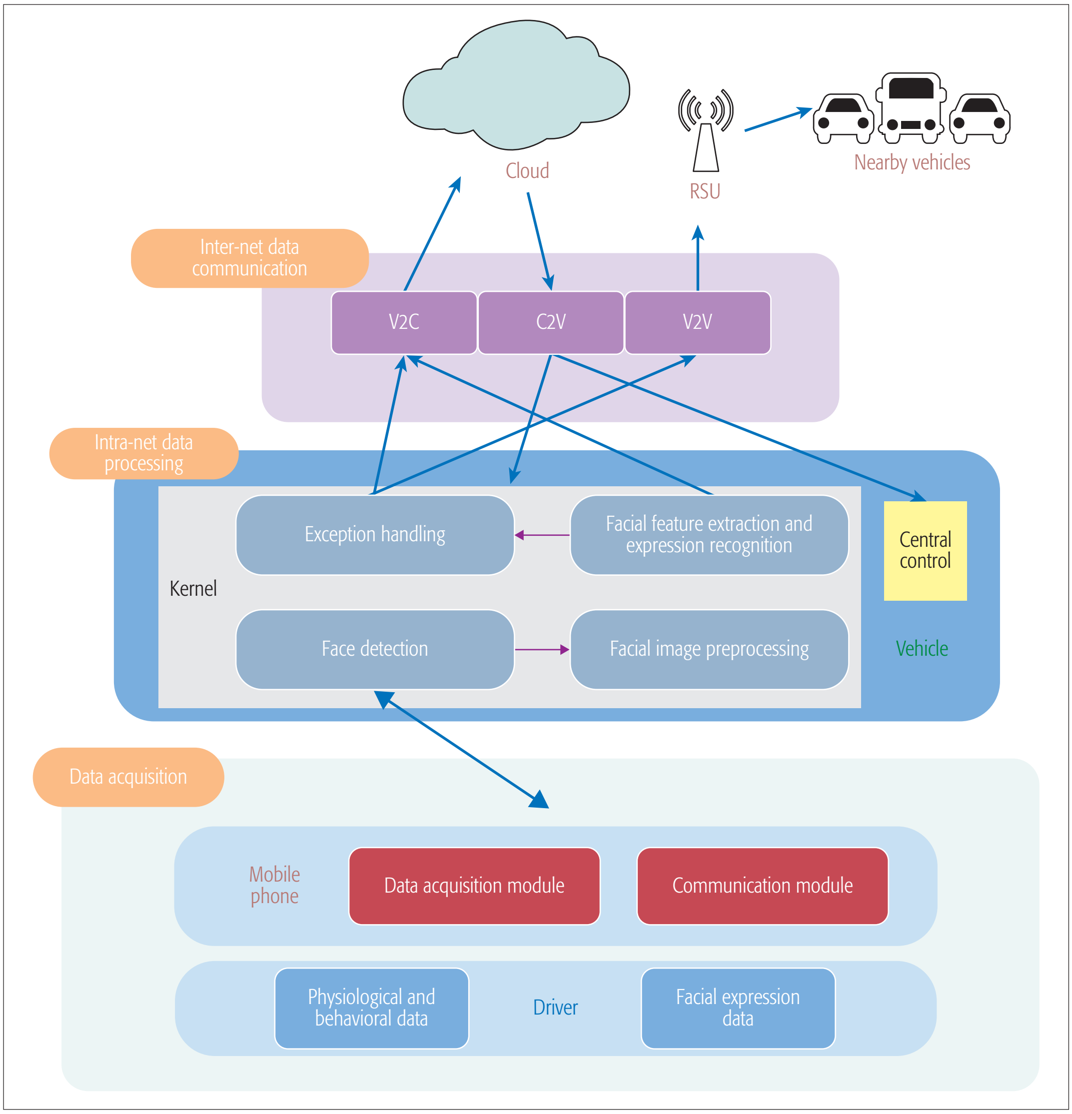

Figure 1. SOVCAN architecture.

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Drivers' Emotional Recognition: In recent years, road congestion and other external factors induced by drivers' emotional abnormalities, leading to open gambling cars or even malicious acts toward pedestrians or other vehicles, have caused major hazards affecting traffic safety. Through the expression recognition and emotional computing method, the system can find drivers' mood swings and effectively avoid road rage.

The remainder of this article is organized as follows. We first present the three-tier architecture of SOVCAN. Specifically, data acquisition, intra-CAN data processing, and inter-CAN data communication layers are described. Then we conclude the article.

SOVCAN Architecture

As shown in Fig. 1, SOVCAN consists of three layers: data acquisition, intra-net data processing, and inter-net data communication.

Data Acquisition: In this layer, drivers' physiological information including responses are collected. The acquisition of physiological signals depends mainly on wearable devices, and physiological response data collection depends on the camera, which can be fused for more comprehensive facial feature extraction and expression recognition [8].

Intra-Net Data Processing: Perceptual data is first transmitted to the onboard intelligence device for analysis, including fatigue identification and emotion perception. If the analysis result of driving state is abnormal, SOVCAN will immediately indicate the car in the vehicular control system for emergency treatment, such as braking, alarming, and speed limiting. Traditional mobile-phone-based computing is different. The vehicle can provide a wealth of resources, particularly energy, and in the SOVCAN computational complexity is not too high. Hence, almost all of the data analysis can be done locally, and the communication overhead can be reduced.

Inter-Net Data Communication: Although most of the data processing can be done within the CAN, in order to retain the driver's data for a long time, we also need to transfer these data to the cloud for preservation. In particular, when the driver changes terminal, it can also download its feature information from the cloud to reduce the time initializing the device. In addition, through the inter-network data communication, we can also send abnormal information to the cloud and nearby equipment to warn nearby pedestrians and take appropriate emergency measures.

It should be noted that, taking into account feasibility and compatibility, this article uses the smartphone as the CAN hub to provide data acquisition, computing resources, network access, and vehicle control system docking.

Data Acquisition

The system mainly collects two types of data: physiological behaviors and facial expressions through a camera. The data for physiological behaviors is to detect driver fatigue and facial expressions for emotion detection.

Physiological and Behavioral Data Acquisition

At present, there are three main methods of fatigue detection: physiological-signal-based detection, traffic-data-based detection, and physiological-behavior-based detection.

Physiological signals may accurately reflect the extent of human fatigue, and electroencephalography (EEG) [9], heart rate variability (HRV) [10], and so on. This can effectively detect the extent of a person's fatigue. However, these intrusive detection techniques rely on special acquisition devices and can reduce the driver's user experience and hinder normal driving. Moreover, some research indicates that the degree of fatigue can be measured by the steering wheel steering angle and lateral position of the vehicle and other variables in the process of driving traffic data [11]. However, because such methods often require retrofitting existing vehicles, such as the installation of sensors, it is difficult for them to be widely used.

Fatigue testing based on physiological behaviors to analyze the drowsiness of people will need to discover people's fatigue states. For example, the behavior of the eyelid and the head can accurately reflect whether the driver has dozed off [12]. Such methods only need an image capture device to record physiological behavior of the driver and can determine whether he/she is in a state of fatigue. This acquisition method can be very compatible with existing vehicles. Thus, the method in this article is to collect drivers' real-time behaviors by placing a cell phone in the cab.

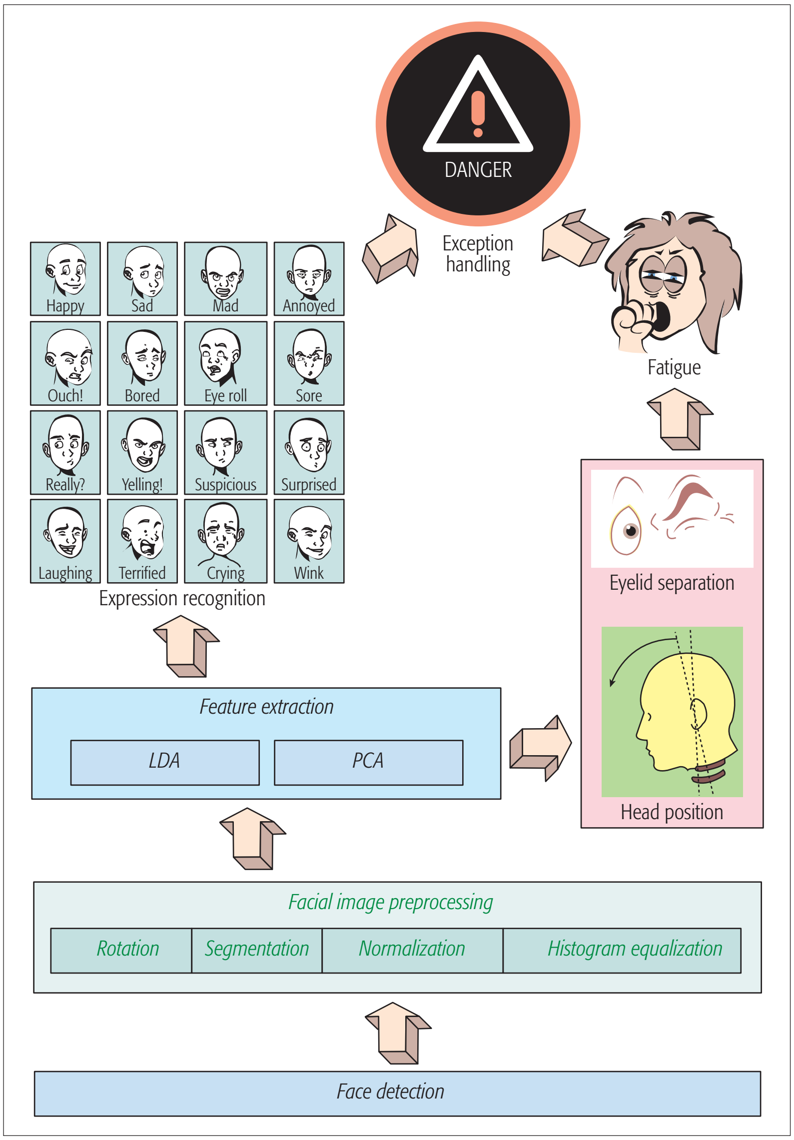

Figure 2. Intra-net data processing.

Facial Expression Data Acquisition

Sentiment analysis is a complex field of study. Currently, it can be divided into three categories:
- Physiology-signal-based emotion analysis [13]
- External-based emotion analysis [14]
- Facial-expression-based emotion analysis [15].

However, based on the way the physiological signal depends on an invasive device to acquire physiological signals, text-based emotion analysis applied to the scenarios has many text resources, such as social networking. These two methods are not applicable to CAN. We only need to record the driver's face image or video and use technologies like image and video segmentation and pattern recognition to analyze the emotional state. The fusion of facial-expressions-based emotion analysis and physiological behavior data collection methods reduce the system overhead and complexity greatly.

Intra-Net Data Processing

The face image acquired by the camera of the mobile phone will be used for fatigue detection and emotion recognition. Its essence is real-time image processing for the driver. As shown in Fig. 2, it includes the following steps: face detection, facial image preprocessing, face geometry extraction and expression recognition, and exception handling.

Face Detection

Face detection is the most important basis for facial expression recognition, which is the basic step for subsequent facial expression preprocessing. Facial expression is the basis of feature extraction and classification. Face detection is to detect the face from an image, extract the face information (eye, nose, etc.), and locate the face position.

Facial Image Preprocessing

Preprocessing of a facial image is essential for expression recognition. First, the result of the above face detection can identify the approximate facial area. Then we can find the location of the eyes and nose in the region. According to these locations, we can correct the face accurately and do operations such as position correction, scaling, and grey level normalization. After preprocessing, we get most of the regions that are related to the expression. Then we need to exclude some areas unrelated to the expression, such as background, ears, hair, neck, and shoulders, and normalize the size and gray value of the obtained expression areas to reduce the light and the impact of light intensity as much as possible.

Facial Feature Extraction and Expression Recognition

We face image preprocessed dimension reduction, feature extraction's main geometric features, such as eyes, nose, eyebrows, mouth, and other positions, and change its position and measure to determine its size andshape, including distance and proportion. One of the most important features is the geometric characteristics of the eye. The location of the eye can determine the relative displacement of the head, so we can determine whether the driver has micro-sleep-induced nodding behavior. In addition, depending on the closed state of the eyelids, the blink frequency of the driver can be used to estimate the degree of drowsiness of the driver. By using the classifier, we can divide the facial geometric feature space into type space. According to the facial expression database, it is accurate to determine in which emotion the driver's current facial expression belongs.

In our proposal, principal component analysis (PCA) and linear discriminant analysis (LDA) are used for facial feature extraction. In particular, PCA is a reproducible approach to reduce data dimension, while LDA is an effective approach to reduce data dimension and classify data.

Exception Handling

Once the driver is in a state of fatigue or an unusual mood, the vehicle terminal will immediately direct the vehicle control system to take some measures such as acknowledging a warning, emergency braking, and speed limiting.

Inter-Net Data Communication

As shown in Fig. 3, inter-network data communications include three approaches: vehicle-to-cloud (V2C), cloud-to-vehicle (C2V), and V2V.

Vehicle to Cloud

With the resources provided by vehicles, a vehicle terminal can complete most local tasks without offloading any to the cloud for processing. However, in the following scenarios, the CAN still needs to transfer local data to the cloud.

Data Uploading: As most of the data collected in the SOVCAN is video, it requires considerable storage space. Although the local equipment can provide a certain storage capacity, it cannot meet the needs of actual use. For example, the smartphone used in the system can provide 32 GB of storage space to store only 480 min of video with resolution of 1280 × 720. In addition, the training of historical data and analysis is available to improve the accuracy of facial expression classification. Therefore, it is necessary to upload the data to the cloud and save them in the cloud.

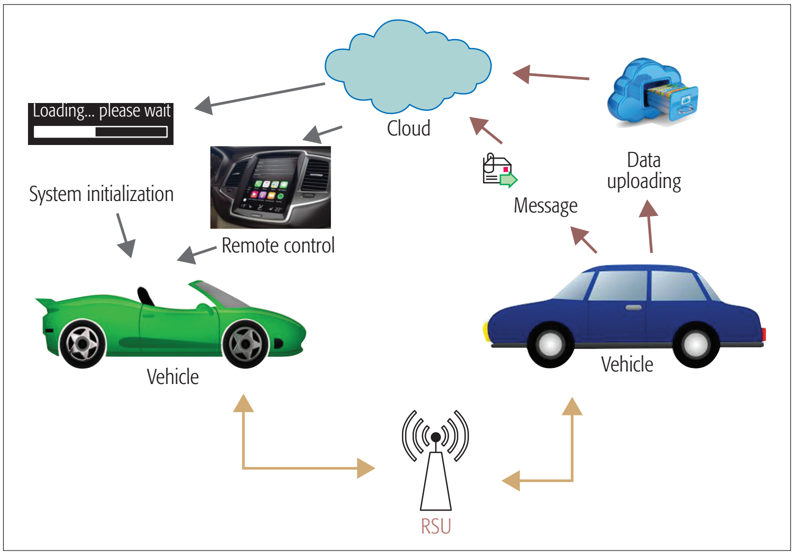

Figure 3. Inter-net data communication.

The real-time requirements for such data transmission are not high, so it mainly uses vehicle-to-RSU (V2RSU), WiFi, and other low-cost means of communication methods.

Message Delivery: It mainly includes requesting messages and exception messages. A requesting message is the message that needs to be sent to the cloud when a vehicular device is initialized or a software error occurs. It indicates that the relevant functional components need to be transferred to the local smart device. When the system finds driver fatigue or abnormal emotion, an exception message will be sent to the cloud for further exception handling. The size of this kind of message is small, and the message is in real time. Hence, in the absence of a low-cost means of communication, it will communicate directly through the mobile network.

Cloud to Vehicle

Depending on the condition of the vehicle, the cloud will also send some data to the vehicle, including system initialization data and remote control messages.

System Initialization: In order to ensure the normal operation of the SOVCAN system, the necessary system function modules must be downloaded from the cloud to the local level, such as to a data processing module, when a vehicle's intelligent equipment is installed or recovered. The scale of the system initialization data is large, and the data is the core of the system. We must exclude the cost and download it to the local level. However, due to its common data, it can be considered to be cached to the equipment at the edge of the vehicular network for improving the download speed and reducing the communication costs.

Remote Control: In extreme cases, when the driver cannot guarantee safe driving, the cloud can send emergency braking commands, controlling the vehicle remotely. The quantity of this kind of control data is small, but its real-time nature is extremely strong. Therefore, no matter how much it may cost to communicate, we must transmit the control information to the onboard intelligent equipment.

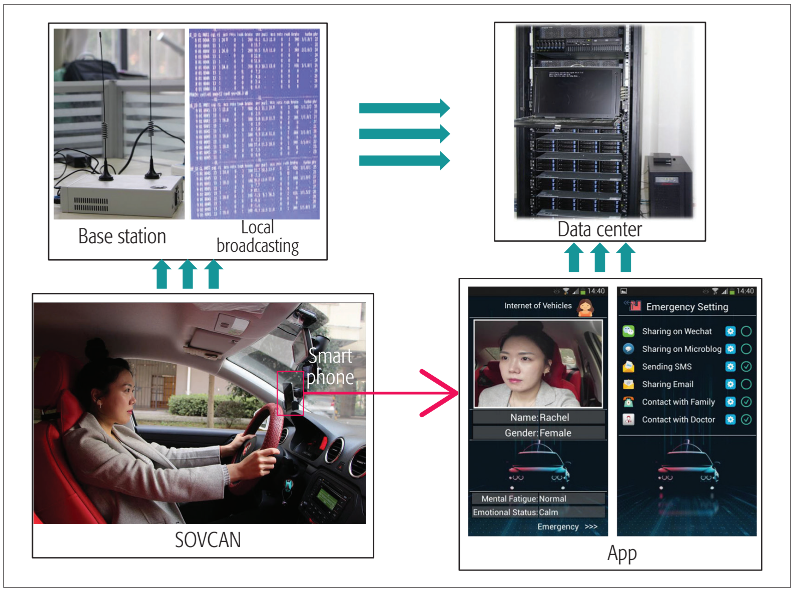

Figure 4. Testbed for SOVCAN.

Vehicle to Vehicle

In addition to the communication between the vehicle and the cloud, there is data communication between vehicles. When SOVCAN detects that the driver's status is abnormal, it will send warning information to nearby vehicles to prompt other drivers to avoid the high-risk driving behavior that the vehicle may incur. Inter-vehicle communication in such scenarios is different from traditional V2V. In conventional V2V, communication between vehicles includes direct communication between vehicles, RSU communication, and base station communication. The V2V communication in SOVCAN is intended to broadcast a reminder message to nearby vehicles. Direct communication between vehicles is too inefficient, and the base station (BS) coverage area is large an hence does not apply to this scenario. Thus, V2V communication uses RSUs to broadcast to nearby vehicles, and the efficiency and cost of this communication are better.

A Testbed for SOVCAN

In order to evaluate the availability of the proposed scheme, we developed a testbed for SOVCAN, which is expected to provide safety-oriented vehicular service based on smartphones through CAN.

Testbed Architecture

As shown in Fig. 4, the SOVCAN-based testbed consists of a smartphone, a BS, and a data center (DC). The detailed mechanism is described as follows.

Smartphone: In SOVCAN, the smartphone plays the most important role to support data sensing and communication. Moreover, with with special software (an Android app) developed by the Embedded and Pervasive Computing (EPIC) Lab at Huazhong University of Technology and Science installed, the smartphone can provide more complex services, including fatigue monitoring, emotion recognition, emergency contact, and so on.

Base Station: In the testbed, a Long Term Evolution (LTE) BS is implemented as an RSU to support V2I and V2V communications. Specifically, through V2I the data is transmitted from the vehicle to the BS, which provides the connection to the cloud. In the V2V communication, once the abnormal statuses are detected and transmitted to the BS, a warning broadcast will be made to the vehicles accessing the BS. In the testbed, Amari LTE is deployed, which includes Iteenb as the LTE access network and LTE mobile management entity (LTE MME) software as the LTE core network involving a service gateway (SGW), packet data network gateway (PGW), home subscriber server (HSS), and so on. The hardware consists of a radio frequency unit, a high-performance computer, and an LTE terminal.

Data Center: In the cloud, a DC, the Inspur In-Cloud Smart Data Appliance, is implemented to provide more storage and computing resources. Specifically, it consists of two main clusters:

1. An admin cluster with 2 nodes, providing 64 CPU cores, 256 GB of RAM, and 3.6 TB of storage
2. A worker cluster with 7 nodes, providing 84 CPU cores, 336 GB of RAM, and 252 TB of storage

In particular, the sensory data is transmitted and stored in the DC as historical data to improve the learning model, while some computation-intensive tasks are offloaded to the DC.

Experiment

In order to verify the availability of SOVCAN in the actual environment, an experiment is designed for evaluation. In this experiment, four volunteers drive the same car deploying SOVCAN about 40 minutes on the same routes. In particular, the route includes normal roads and a long tunnel.

Figure 5 illustrates the recognition accuracy of SOVCAN in this experiment. Through the experiment, the recognition accuracy in the tunnel is obviously lower than that in the normal environment, because the light is darker in the tunnel, which causes a significant negative effect on image processing. Of course, it is simple to verify the availability of SOVCAN, so we do not design more comprehensive experiments including the consideration of more traffic conditions and the external environment, or comparison with other related approaches.

Open Issues and Future Directions

Although the testbed is able to provide the essential services for vehicle safety, more details are not considered for improving the availability and performance.

Low Delay: In order to improve the accuracy of fatigue monitoring and emotion recognition, more physiological and psychological data should be sensed, processed, and transmitted through SOVCAN. In particular, safety message transmissions have a very low delay constraint, such as less than 1 ms.

Frequent Handover: In SOVCAN, the communications between the vehicles, RSU, and cloud are frequently handed over, which is a huge issue for providing reliable communication.

Highly Efficient Services: For the future CAN, vehicular smart devices are not only the control platform but also entertainment centers for users. Different multimedia services need to be provided by vehicular networks. It is a great challenge to improve the service efficiency.

Robustness: The experiment illustrates that recognition accuracy is strongly related to external factors. For example, some accessories on a driver's face significantly affect facial expression recognition, such as glasses or a scarf. Moreover, the quality of the sensory image is limited under some circumstances, such as on bumpy roads or in insufficient light, which considerably lower the system performance.

Conclusion

The rapid development of vehicular networking has brought revolutionary changes to society, covering almost every aspect of daily life. More and more applications, systems, and services for vehicular networking are being expanded. This article proposes SOVCAN, which aims to detect drivers' fatigue and mood swings in CAN to guarantee safe driving. Specifically, according to the different requirements of data communication in SOVCAN, we use SDN technology in three different scenarios: V2C, C2V, and V2V. According to the different demands for real-time communication, efficiency, and cost, appropriate communication is selected in the SDN-based architecture.

In our current work, there are still some technical challenges. In particular, the most critical problems are lack of robustness in facial feature extraction and expression recognition, road bumps obscuring the collection of facial images, and the complex cab background affecting the accuracy of detection in the network data processing. Therefore, in the future, we will try to use non-invasive wearable technology under the premise of keeping the normal driving behavior such as smart clothing to improve the robustness of the system.

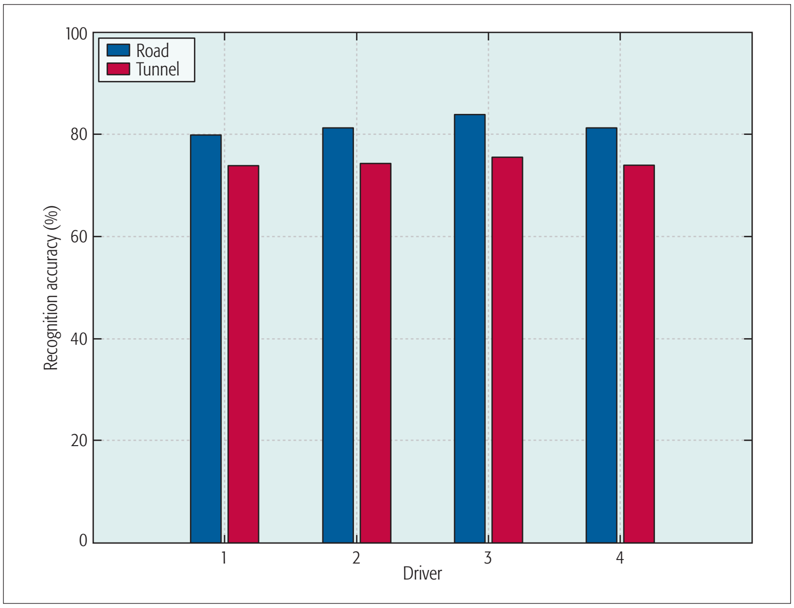

Figure 5. Recognition accuracy of SOVCAN.

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