Classifications of Driving Patterns Using a Supervised Learning Method for Human-Vehicle Interaction

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Abstract: Enhancing the safety of drivers is one of important issues in a driving assistant system (DAS). In order to solve this issue, the situation information of a vehicle should be recognized. In this paper, we present Discrete Hidden Markov models (DHMMs) to classify five driving patterns which are essential features for recognizing the situation information of vehicles. A virtual vehicle simulator was developed to collect the raw data of the driving operation, and each DHMM was learned from the obtained training data. The structures of the DHMMs were experimentally selected using a cross-validation process with the results showing 89.8% classification accuracy.

1 Introduction

Since the advent of intelligent vehicles, enhancing the safety of the driver is one of the important issues pertaining to a driving assistant system (DAS). The purpose of a DAS is to prevent drivers from encountering dangerous situations by controlling their vehicles or notifying them of the current vehicle information by means of warning alarms. There have been many types of DASs developed, such as the FRMS (front rear monitoring system), LDWS (lane departure warning system), LKAS (lane keeping assist system), SOWS (side obstacle warning system), and LCDAS (lane change decision aid system), etc. Although they have many advantages when used to detect dangerous situations and to control a vehicle actively when a driver cannot recognize dangers in advance, they still have several limitations as discussed below.

First, these systems do not detect the current situations of a vehicle and driver, such as urgent, distraction, abnormal and dangerous situations, as inaccurate information pertaining to the detected situation can confuse drivers and because the detection process is complicated. Second, without the situation information, the aforementioned methods cannot determine the priority of information to be delivered to the driver. Nevertheless, classifying the situation of the vehicle using the raw data of the vehicle (e.g., the steering angle, speed, yaw rate, and brake pedal information) is important to improve the safety and performance in a wide range of applications. For example, LDWS detects the lane using vision data mainly in order to warn the drivers of dangerous behavior by a vehicle, but this method is not foolproof in bad weather. With the ability to recognize the current situation, vehicles can warn the driver by referring to the situation information regardless of a lane departure. From the viewpoint of HVI (Hunam-Vehicle Interaction), situation information can help a vehicle to distinguish the necessary information from all information in the current environment so that a driver can recognize essential information efficiently.

The vehicle situation can be recognized by converging driving patterns, the driver, and the surrounding information. Driving patterns are composed of many actions, such as cornering, lane changes, following, overtaking, stopping, and speeding, among others. In the case of lane-change, there is a research finding the lane change maneuvers of a probe vehicle itself using Differential Global Positioning System (DGPS) data and multiple probe vehicle trajectories[1], and there is a research to estimate time-varying lane-changing fractions and queue lengths using stochastic system modeling[2].

In the case of car-following, there is a research for evaluating a car-following model and comparing the behavior predicted by the GM models with the behavior observed under the real world situation[3], and there is a research proposed driver-behavior modeling to anticipate car-following behavior in terms of pedal control operations in response to the observable driving signals, such as the own vehicle velocity and the following distance to the leading vehicle[4]. In the case of left or right turning, there is a research applied to unusual right-turn driving behavior prediction at an intersection with an experiment on a driving simulator[5]. Vehicle situations are a more superordinate concept than driving patterns.

In this paper, we classify the driving patterns of lane changes and cornering, which can be used to recognize vehicle situations. In order to classify these driving patterns, an approach involving a discrete hidden Markov model (DHMM) is applied. The HMM, a supervised learning algorithm, has become increasingly popular in the last many years. and HMM representing sequences of states that have structure in time, such as speech recognition[6, 7], handwriting[8], hand gestures, And also hidden Markov models is a effectiveness processing to describe distributions over meaningful state sequences with the models using vehicle signals[9]. The method has two strong advantages in this study. First, DHMMs are very rich in terms of their mathematical structure and hence can form a theoretical basis for use in a wide range of applications. Second, the models, when applied properly, work very well in practice. The DHMM procedure is discussed in Chapter 2.

There are similar studies regarding the enhancing of safety issues in DAS. Kannan et al. proposed the intelligent driver assistance system (I-DAS)[10] for safety warning messages during time-critical situations using an ontology approach. In addition, Jin[11] proposed a novel safety lane change model to reduce traffic accidents during conscious lane changes by vehicles on highways under dangerous conditions. These examples rely on different approaches to solve safety issues in DAS, but they do not consider the situation information deeply. Moreover, the number of driving patterns is limited.

2 System Architecture

2.1 Virtual Vehicle Simulator Environmental

In order to collect raw data pertaining to a vehicle, in this case the steering angle, speed, yaw rate, gas pedal information, brake pedal information and the three-dimensional position with a sampling time of 100ms, a virtual vehicle simulator is developed. This virtual vehicle simulator was designed with one monitor as a display and a Logitech force-feedback wheel joystick with two state pedals (one for acceleration and the other as a brake), as depicted in **Figure 1**. The input devices for steering and the pedals are tuned to simulate a real vehicle as much as possible. This virtual vehicle simulator uses a three-dimensional driving environment, as depicted in **Figure 2**, which satisfies the verification of driving patterns such as lane changes, cornering, overtaking and, intersection patterns. Several barriers are placed on the track randomly for lane changes and stopping patterns.

2.2 Supervised Learning Algorithm.

Driving patterns are composed of many actions, such as cornering, lane changes, following, overtaking, stopping, and speeding, etc. This research classifies the driving patterns of lane changes and cornering because these patterns occur more frequently than other patterns when driving. Furthermore, they are considerably related to dangerous situations.

In this study, five driving patterns, as shown in Table 1, are classified by a supervised learning method. As depicted in **Figure 3**, the learning process is composed of two phases. The first phase involves vector quantization for discretizing continuous input data, and the second phase involves the learning of the DHMMs, each of which denotes each driving pattern separately.

Figure 1. Experiments environment 3-Dim. Driving simulator and Logitech wheel joystic with 2 state pedals

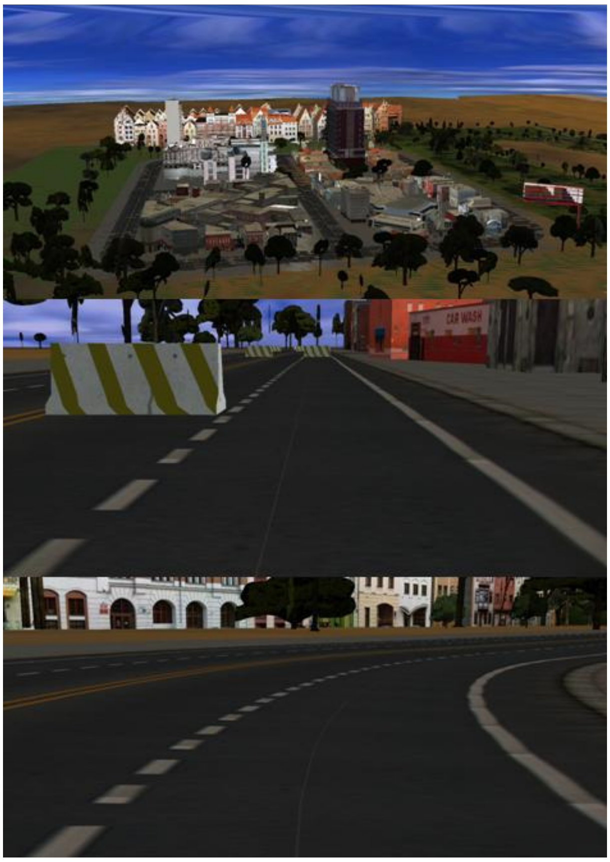

Figure 2. The virtual vehicle simulator

TABLE 1. Five driving patterns

	Left	Neutral	Right
Driving Patterns	Lane change Cornering	Neutral	Lane change, Cornering

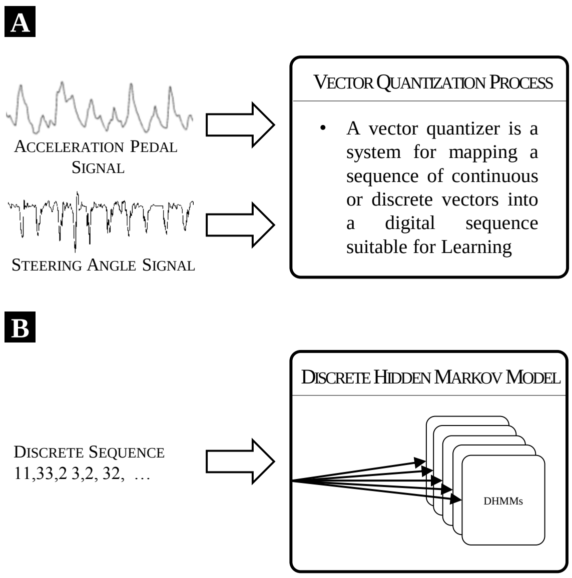

Figure 3. Supervised learning overall diagram

3 Experiments and Results

3.1 Data Acquisition

The first experiment was done for the purpose of evaluating the characteristics of normal driving patterns and to formulate a training data set. Subjects were 10 normal people aged 20~30 years (males, licensed). The data acquired from the first experiment were from a total of 50sets of five driving patterns. Subjects conducted five trials each. The experimental procedure is described below.

- Step 1: Brief explanation of the experiments and the virtual vehicle simulator
- Step 2: Give some time to become familiar with the track
- Step 3: Circuit driving for data acquisition (CW and CCW, respectively)
- Step 4: Repeat Step 1 through Step 3 five times

The second experiment sought to gain a variety of training data. All subjects drove on an identical track with constraints that diversified the driving patterns. The data acquired from the second experiments were used to formulate 50 sets of five driving patterns. The procedure and constraints of the second experiment are described below.

- Constraints: Each subject should avoid barriers and remain in his lane for a limited time (one minute per circuit driving).
- Step 1: A brief explanation of the constraints
- Step 2: Give some time to for the prepare experiment
- Step 3: Circuit driving for data acquisition (CW and CCW, respectively)
- Step 4: Repeat Step 1 through Step 3 five times.

3.2 Vector Quantization.

The first phase of the learning process is vector quantization. This is necessary for mapping two continuous sets of raw data into a discrete value suitable for input into a DHMM[12]. Seven-level threshold values are used, as shown in table 2. The vector quantization results are depicted in **Figure 4**. In this figure, black cells denote a high frequency of occurrences while white cells represent a low frequency of occurrences. The figure shows the well-distributed characteristics of each pattern

TABLE 2. The threshold for vector quantization

Input Sequance	Threshold Level
Steering angle	Under -40 degree
	Over -40 degree ~ Under -12 degree
	Over -12 degree ~ Under -5 degree
	Over -5 degree ~ Under 5 degree
	Over 5 degree ~ Under 12 degree
	Over 12 degree ~ Under 40 degree
	Over 40 degree
Acceleration Pedal	Under 18 %
	Over 18 % ~ Under 24 %
	Over 24 % ~ Under 29 %
	Over 29 % ~ Under 43 %
	Over 43 % ~ Under 50 %
	Over 50 % ~ Under 60 %
	Over 60 %

3.3 Baum-Welch Learning Algorithm.

The second phase is the learning process, and this uses the Baum-Welch algorithm. Each DHMM is learned from an observation sequence in the training data obtained from the above experiments for each driving pattern. In generally, the Baum-Welch algorithm incurs an overfitting problem. Therefore, we undertook a cross-validation process and evaluated the appropriateness of the learned DHMMs according to the number of hidden states. As a result, five hidden states were selected to avoid the overfitting problem. **Figure 5** shows the cross-validation results with two to eight hidden states. **Figure 6** presents a confusion matrix of the test data as evaluated by the learned DHMMs. The accuracy of the classification is 89.8%.

3.4 Results of Real-Time Classification

For a real-time classification of the driving patterns, we implemented the five learned DHMMs into a virtual vehicle simulator. Time-series data pertaining to the steering and acceleration pedal were acquired in real time from the virtual vehicle simulator and were stacked up to 50 sequential datasets with a sampling time of 100ms.

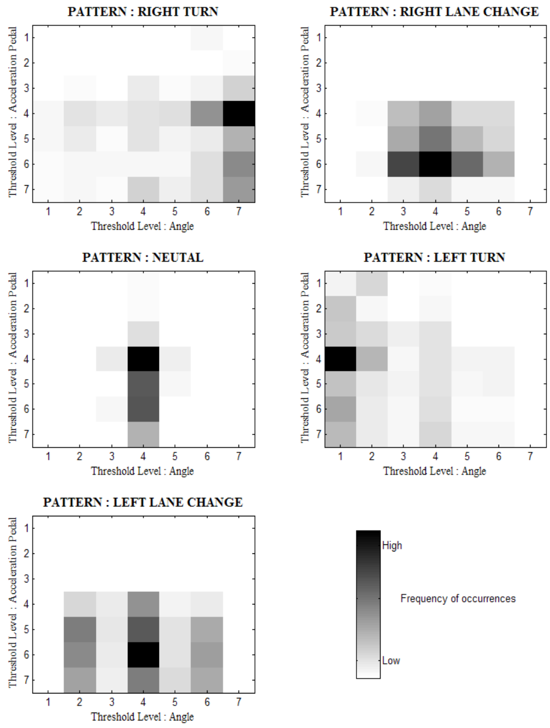

Figure 4. A frequency map of each state

The input sequence was discretized by a vector-quantization process and its similarity with each driving pattern was then evaluated using the Viterbi algorithm. Finally, the averaged Viterbi distance of each DHMM was compared to that of the other models, after which the i^{th} DHMM with a minimum distance was selected as the current driving pattern:

$$\text{Current Driving Pattern} = \arg\min_{i}(\text{Average Viterbi Distance})$$

Figure 7 represents the average Viterbi distance of each DHMM model with respect to time.

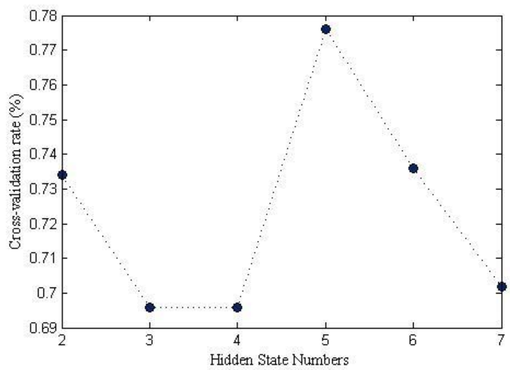

Figure 5. A cross-validation result

	Left Lane Change	Left Turn	Neutral	Right Lane Change	Right Turn
Left Lane Change	0.89			0.05	0.06
Left Turn		1			
Neutral	0.03	0.04	0.8	0.13	
Right Lane Change	0.09		0.04	0.87	
Right Turn		0.07			0.93

Figure 6. The confusion matrix with five hidden States

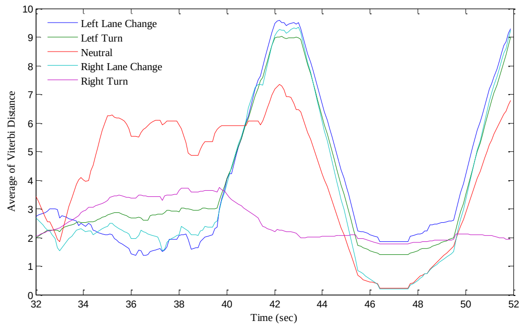

Figure 7. The average Viterbi distance of each DHMM

4 Further Works and Conclusion

In this paper, five driving patterns were investigated in order to recognize situation information, which is useful when seeking to enhance driver safety. We applied a DHMM method to classify the five driving patterns, which resulted in classification rates of 89.8%. The training and test data were obtained from a virtual vehicle simulator and the learned DHMMs were successfully embedded for real-time recognition. In order to understand driving situations, following further works will be explored. First, a variety of patterns should be classified, as these are related to safety and performance of a driving assistant system. These can include starting a car, using the seat belt, checking the gas gauge, and setting the temperature. Second, constructing reaction model is necessary to provide proper information to drivers for application in the field of Human-Vehicle Interaction.

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