은닉 마르코프 모델을 이용한 인간 운전 행동 양식의 모델링 및 인식

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Modeling and Recognition of Human Driving Behavior using Hidden Markov Models

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ABSTRACT

This is an attempt towards building a probabilistic model of human driving behavior using hidden Markov models (HMMs) with continuous observations. After collecting needed driving data during a simulated driving task, the proposed segmentation and clustering algorithms are applied to group similar segments into nine different clusters. For each cluster one HMM is trained in a way to have maximum likelihood measure. In recognition phase, a sliding window of an unknown driving data is fed into each HMM, and the one with highest likelihood measure is marked as chosen cluster. The experimental results confirm the efficacy of the proposed approach by revealing recognition accuracy exceeding 85%.

1. INTRODUCTION

It has been long time, researches in various application areas from robotics to virtual reality, are looking for a reliable model which can emulate human dynamic behavior. If such a model can be constructed, the acquisition and recreation of human behavioral skills can be achieved. As the human psychomotor movements are inherently stochastic, a different set of actions takes place every time the same task is performed by the human operator. So a framework is needed, regardless of applied actions, to extract the inherent characteristic of a behavioral skill. Since there is no analytical way to derive human skill, we have to model it through observation, and learning from experimentally provided training data. A stochastic method which is frequently used to define the skills and model their uncertainties is hidden Markov model (HMM). An HMM can easily decode and abstract the human skill in both non-observable mental states, and observable task states.

This paper is organized as follows: in the next section, related work is briefly reviewed. In section 3, an overview of the proposed system is given. Experimental results are presented in section 4 and conclusion and future work in section 5.

2. PREVIOUS WORK

Hidden Markov models have been used extensively in research on automatic speech recognition, gesture recognition and later in learning human action and transferring human skills for tele-robotics applications [1,2,3]. In driving applications, Pentland and Liu developed a computational state-based model of driver behavior using HMMs [4]. Xu et al. proposed a framework of capturing and modeling dynamic human driving behaviors to identify the drivers' identity [5]. In [6] an HMM framework is used to recognize different driver maneuvers. In another work, HMMs were used to recognize maneuvers and detect the driver distraction or driver faults using a hierarchical approach [7,8]. Berndt et al. addressed designing advanced driver assistance system and investigated early driver intention inference with HMMs by observing accessible vehicle and environment signals [9].

Modeling driving shares some aspects with speech recognition. From the sensor point of view, driving in a car produces a stream of parameters from various different sensors. Thus the sensor stream needs to be segmented in time into different context classes that are relevant to driving. The "sentence" of driving should be segmented into "words" of driving, that is,

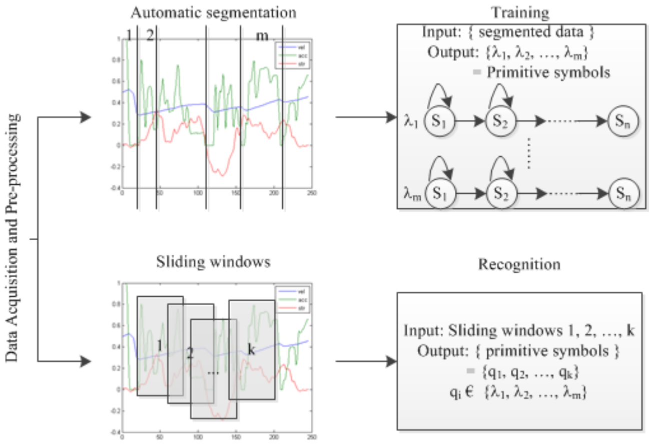

Fig. 1. The building-blocks of the proposed system

maneuvers. However, no "phonemes" exist for driving. Thus each different maneuver has to be modeled as a discrete entity with no shared parts. In [10] the authors tried to discover such subunits for the purposes of modeling driving sensor data. The subunits are named "drivemes". In another attempt [11], the authors assumed that the driving time series signal is a sequence of driving patterns. So the measured signal has to be segmented into the driving patterns in order to symbolize the driving skills. The authors emphasized that each segmented driving pattern data is classified into an HMM which outputs the largest likelihood that the HMM generates the driving data, and the driving pattern data is used as a training data for the HMM. These HMMs extract features of the driving patterns. They named the HMMs, proto-symbols since the HMMs form to the origins of symbols.

3. SYSTEM OVERVIEW

The building-blocks of the proposed system are given in Fig. 1. First required driving data is collected and pre-processed, then they are segmented and similar segments are grouped into a number of predefined clusters. Next, grouped data in each cluster is used for training one HMM. At the end by feeding sliding windows of unknown driving data into trained HMMs, their performance in recognition correct clusters is evaluated.

3.1. Experimental Setup

The driving simulator we used to conduct experiments consists of a hardware set, Logitech G25 Racing Wheel, and a simulation program developed using Irrlicht Engine, an open source graphic toolkit, and Newton Game Dynamics, a physics engine. The subject driver is asked to drive the vehicle along the driving track repeatedly for at least 20 times. The subject driver only had access to accelerator pedal to increase/decrease the speed and steering wheel to rotate left/right. During the driving, the required driving signals such as accelerator pedal position, steering wheel angle, velocity and heading of the vehicle and two-dimensional x-y position coordinates of the car are recorded in every 10 msec.

3.2. Segmentation and Clustering

The driving time-series data is segmented based on a criterion inspired by real driving situation. Typically velocity and heading of a car is the only features can be manipulated by the driver. Having this in mind, we detected the time-points in which the driver tries to change velocity and/or heading. For this end, the local exterma of the velocity and heading signals are determined separately. If we name the first order derivative of the mentioned signals as translational and rotational acceleration respectively, then the local exterma are occurred whenever these accelerations cross the zero axes. To numerically compute the first order derivative, the method of central estimate is implemented in the Matlab program.

After segmentation we needed a criterion to categorize similar segments into a limited number of clusters. For this end, we made an assumption on translational and rotational accelerations. By defining a well-suited threshold value, each acceleration signal is approximated and discretized into three levels: greater than threshold, between minus and positive value of threshold, and smaller than minus threshold. For the purpose of annotation of each region, we used +1, 0, −1 respectively (Fig. 2. a, b). This consideration leads us, in combination, to a total 9 different clusters (TABLE I).

TABLE I. 9 different clusters

		Translational acceleration		
		+1	0	−1
Rotational acceleration	+1	1	4	7
	0	2	5	8
	−1	3	6	9

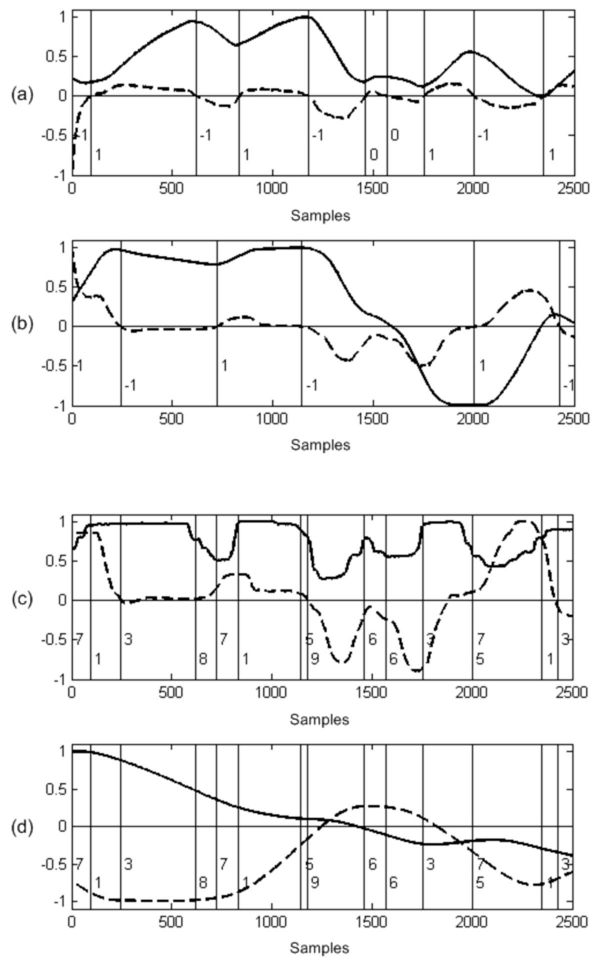

Fig. 2. a) segmentation based on velocity, solid: velocity, dashed: translational acceleration. b) segmentation based on heading, solid: heading, dashed: rotational acceleration. c) segmentation based on velocity and heading, solid: accelerator pedal position, dashed: steering wheel angle, d) solid: x-coordinate, dashed: y-coordinate.

3.3. Hidden Markov Modeling

Now that the driving signals are segmented and categorized into 9 different clusters, we are ready to start training one hidden Markov model (HMM) corresponds to each cluster. Amongst all recorded driving signals, a two dimensional training data set consisting acceleration pedal position and steering wheel angle is chosen to train HMMs.

Before starting training HMMs, we should make decision about type of HMM, its topology and the number of hidden states. In case of our application, we chose continuous HMMs with left-to-right topology and 6 hidden states. Usually in continuous case a mixture of multivariate Gaussian density functions are fit onto observations. Experimentally we found that a mixture of two univariate Normal density functions are enough for our two dimensional observations. Using Kevin Murphy's HMM Toolbox, the HMMs are trained and then used to recognize an unknown driving data by feeding sliding windows with the length of 16.

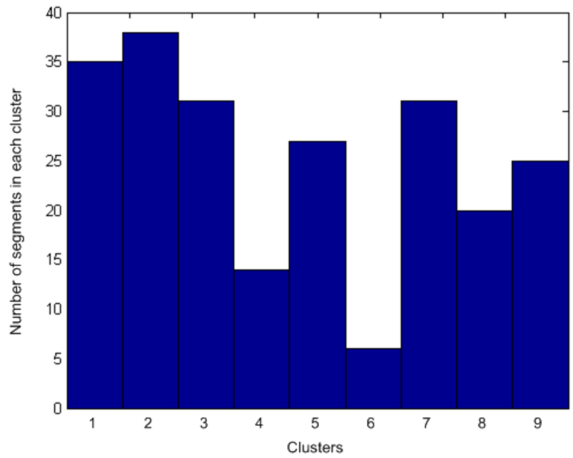

Fig. 3. Histogram plot of the number of segments in each cluster.

4. RESULTS

The result of segmentation is given in Fig. 2. The first two plots show the regions result in segmentation based on local exterma of the velocity and heading signals individually. As we can see, the accelerations value and corresponding annotation is either positive (+1), negative (-1) or 0, according to the criterion mentioned before. To be more specific, +1 means that the translational or rotational acceleration is positive (greater than the threshold value); hence the velocity or heading is going to increase. The results of combined segmentation are given in the last two plots. This time the annotation is based on the index of 9 different clusters each segment belongs (TABLE I). Data segments with similar index are grouped into one cluster, later to use as training data set.

One amazing result can be drawn from the histogram plot of the number of segments in each cluster (Fig. 3.). It can be seen that the number of segments belong to categories #4 and #6 is considerably less than others. Having no translational acceleration (which means keeping the speed constant), the driver barely intends to turn the steering wheel. Most likely this is about the part of driving track that the driver has a long straight road in ahead.

After training the HMMs, they are used to recognize an unknown test data set. In recognition phase, sliding windows with size of 16 and 50% overlap are fed into trained HMMs. According to our segmentation and clustering method, each window belongs only to one cluster. If the index of the window and the index of HMM with maximum likelihood value is the same then the recognition is done accurately. The classification rate regarded to each model is given in TABLE II. As we can observe, the average overall correct classification ratio is about 85%. This proves that the constructed HMMs are being able to recognize the correct category with about 85% certainty.

TABLE II. Correct classification rate

HMM#	1	2	3	4	5
Rate%	90.2	93.7	89.1	80.3	88.3
HMM#	6	7	8	9	AVG
Rate%	77.7	89.6	80.1	82.5	85.7

5. CONCLUSION and FUTURE WORK

We have shown that using an appropriate segmentation method and clustering criterion, we are being able to model human driving signals as a set of HMMs. The proposed segmentation algorithm can be improved by considering more detail information about translational and rotational accelerations. Currently we just assumed that each acceleration signal is discretized into three levels. The depth of discretization can be increased by adding more steps. The current effort focused on recognizing short-term features such as increasing/decreasing speed or turning left/right. It can be extend to recognize long-term driving maneuvers by training another set of HMMs on short-term HMMs. The final goal of the research team is to make use of the proposed framework to capture the driving skills from an expert driver and teach them to a novice driver in a multi-modal feedback system.

6. ACKNOWLEDGEMENT

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