은닉 마르코프 모델과 GMM 기반 클러스터링을 이용한 인간 운전 패턴의 모델링

Human Driving Patterns Modeling using Hidden Markov Models and GMM-based Clustering

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Abstract In this work the use of two stochastic methods, hidden Markov models (HMM) and Gaussian mixture models (GMM), is presented to construct a reliable model for human driving patterns. After collecting driving signals including velocity and heading of the vehicle using a simulated driving task, translational acceleration and rotational velocity as two most important features are extracted. Then a segmentation method based on detection the local extrema of the velocity and heading signals, divides driving data into a number of segments. By studying histogram plot of the extracted features, it is found a mixture of three and four univariate Gaussian mixture models can be fitted onto translational acceleration and rotational velocity respectively. Considering each mixture component as a cluster, in total we have twelve different clusters in combination. Segmented data are categorized into these clusters; forming training data set for HMMs. The parameters of one HMM for each cluster are optimized using the obtained training data set. The experimental results reveal that the trained HMMs can recognize correct clusters with about 71% accuracy.

Keywords: driving patterns, HMM, GMM, stochastic modeling

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1. Introduction

It is long time, researches in various application areas from robotics to virtual reality has been 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 human actions are inherently stochastic, there is no analytical approach exist for study them, therefor we have to model them 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.

2. Previous Work

Hidden Markov models have been used extensively in research on automatic speech recognition and later in human/machine interaction framework. In driving applications, Pentland and Liu developed a computational state-based model of driver behavior using HMMs [1]. In [2, 3], HMMs were used to recognize maneuvers and detect the driver distraction or driver faults using a hierarchical approach. Berndt et al. addressed designing advanced driver assistance system and investigated early driver intention inference with HMMs by observing accessible vehicle and environment signals [4]. Some researchers tried to address the problem by drawing an analogy with speech recognition systems in which in lowest level, basic components of a speech called “phonemes” are recognized by trained HMMs. In [5] the authors attempted to discover such subunits for the purposes of modeling driving sensor data. The subunits are named "drivemes". In another effort [6], 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. Method

To address the problem of interest we made use of hidden Markov models as the probabilistic modeling tools. An HMM is a doubly stochastic process with an underlying stochastic process that is not observable, but can be observed through another set of stochastic processes that produce a sequence of observed symbols. Hidden Markov Models are especially known for their application in 1D pattern recognition such as speech recognition and sequencing problems in bioinformatics. In our application, driving time-series signals are modeled using a set of HMMs. The block diagram of proposed system is given in Fig. 1.

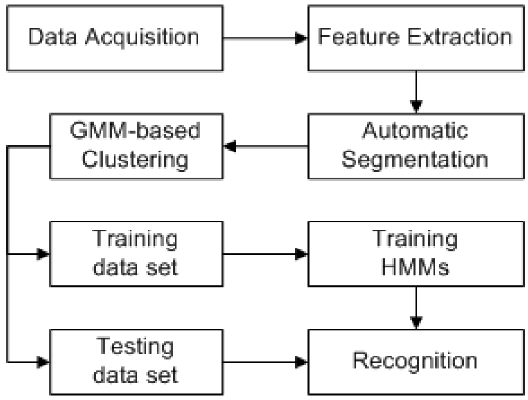

Fig. 1. Block diagram of proposed system

To collect needed driving signals, a driving simulator is customized based on Logitech G27 racing wheel. The subject driver is asked to drive around the track repeatedly for several times. Driving signals including velocity and heading of the vehicle are collected during the driving. From the fact that driving is nothing just controlling and manipulating the velocity and heading in all the time, their first-order derivative, namely translational acceleration and rotational velocity respectively, are extracted as the two most important features which best represent the intentions of the driver. Then an automatic segmentation method based on the detection of the local exterma of velocity and heading signals is performed to divide the driving data into a number of distinct segments (Fig. 2.).

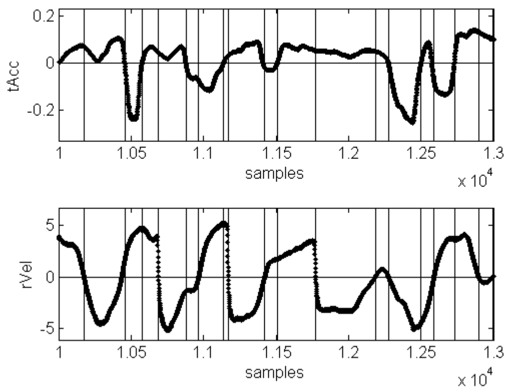

Fig. 2. The result of segmentation, vertical lines showing the boundaries of segments. tAcc: translational acceleration, rVel: rotational velocity.

By the fact that not all segments are different, to cluster similar segments, a probabilistic method based on Gaussian mixture models is employed. By studying histogram plots of extracted features, we found that a mixture of three univariate Gaussian probability density functions can be well-suited onto translational acceleration and a mixture of four onto rotational velocity (Fig. 3.). Considering combination of three and four components for the features, leads us to a total number of twelve different clusters. To do clustering, each feature data segment are examined against one of the components of the correspond GMM. The one with highest probability is chosen as the belonging cluster. A 2-fold cross-validation is hired to prepare training and testing data sets. Correspond to each cluster one HMM is trained till its parameters are optimized. The type of HMMs is chosen to be as continuous observation with left-to-right topology and nine hidden states. To evaluate the performance of trained HMMs, consecutive sliding rectangular windows with the length of 16 and 50% overlapping on testing data set is fed into each HMM, the one with highest likelihood measure is marked as the belonging class (cluster). It is shown that the correct classification ratio up to 71% in average is achievable (Fig. 4.). The average ratio is highly affected by the performance of HMMs #4, #5. If we ignore their participation the average ratio will rise to 78%. Main reason for their low performance is the lack of enough training data samples. In each GMM there is one component with very small variance, the narrowest one in both histogram plots in Fig. 3. As an immediate result the number of data samples in corresponding cluster will be small. In lack of enough training data samples, the parameters of HMMs cannot be optimized well.

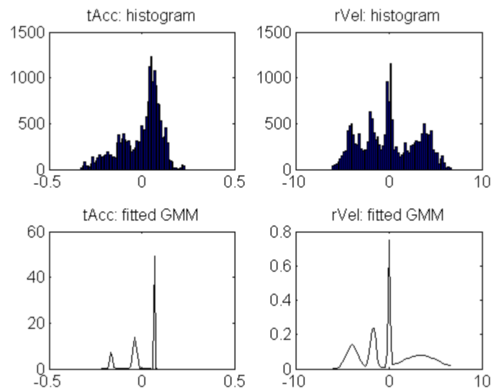

Fig. 3. Histogram plots and correspond fitted GMM. tAcc: translational acceleration, rVel: rotational velocity, x-axes: range of bins.

Each cluster has some physical meaning attached. By labeling GMMs' components as {1,2,3} for tAcc and {1,2,3,4} for rVel from left to right, we will have twelve clusters by their combination. For example for the first cluster which is equivalent to the most-left components in both GMMs, one can interpret as decreasing speed (observing negative acceleration) while having strong intention to turn left (considering very negative rotational velocity).

4. Conclusion

We have shown the efficacy of using two stochastic methods to recognize human driving patterns, GMM for clustering segmented data, and HMM for modeling clustered data. To this end an appropriate segmentation method based on detection of local extrema on velocity and heading signals was used. By fitting a GMM to each extracted feature, twelve different clusters were formed; later one HMM for each cluster was trained. The trained HMMs have shown a performance of 71% in average in recognition correct cluster which can be increased by collecting more training data samples.

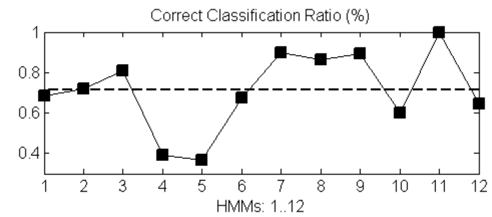

Fig. 4. Individual (solid square) and average (dashed line) correct classification ratio

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