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Human Driving Behavior Recognition Based on Hidden Markov Models

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***Abstract*— Automobiles are by now indispensable to our personal lives, but the problem of car thefts threatens the automobile security seriously. In this paper we present an intelligent vehicle security system for handling the vehicle theft problem under the framework of modeling dynamic human behaviors. We propose to recognize the drivers through their driving performances and hope this can help reduce the number of car thefts significantly. Firstly we describe our experimental system—a real time graphic driving simulator—for collecting and modeling human driving behaviors. Using the proposed machine learning method hidden Markov model (HMM), the individual driving behavior model is derived and then we demonstrate the procedure for recognizing different drivers through analyzing the corresponding models. Then we define performance measures for evaluating our resultant learning models using a hidden-Markov-model-(HMM)-based similarity measure, which helps us to derive the similarity of individual behavior and corresponding model. The experimental results of learning algorithms and evaluations are described and finally verify that the proposed method is valid and useful against the vehicle thefts problem.**

***Index Terms*— Vehicle security, Human behavior modeling, Machine learning, Intelligent systems.**

A. Motivation

In the last few years, modeling dynamic human behaviors is becoming an increasingly popular paradigm in many different research areas, however, the application for security is less investigated. Nowadays, vehicle theft is a reality. According to the National Insurance Crime Bureau, a vehicle is stolen every 25 seconds in the U.S. and each year along over 1.2 million vehicles were stolen across the country, causing 8 billion US dollars in losses. Therefore the work on vehicle security is significant.

In this paper, we focus on the research of utilizing dynamic human behavior models for the vehicle security (preventing from being stolen) application. Since alive biometrical features in dynamic human behaviors are unique and hard to duplicate comparing with other patterns in common security applications, such as password, fingerprint, facial recognition, etc. Therefore, dynamic human behavior models can be utilized as a secure key for the vehicle security application.

A methodology based on modeling dynamic human driving behaviors with hidden Markov models (HMMs) is proposed in this paper. It means that a car with this technology embedded can identify the driver through the driving performance in real time. When an illegitimate driver come to use the car and the demonstrated driving behaviors do not match the specified model, the car will automatically stop running and deliver alarm signals accordingly.

B. Related Work

In the past decade, significant researches towards learning skills directly from human have been conducted primarily by Asada's group at MIT[1], the Navlab group at CMU[2] and our group at CUHK[3][4]. In [1], a debarring robot is controlled through an associative neural network which maps process parameter features to action parameters from human control data. In [2], Pomerleau implements real-time road-following with data collected from a human driver and a static feedforward neural network learns to map coarsely digitized images of the road ahead to a desired steering direction. In [3] and [4], we concentrate on modeling closed-loop reaction skills where sensory feedback to the human is required to successfully complete the task and abstracting models of dynamic human control strategy (HCS), a particular subset of human reaction skills. All these studies can model human driving behaviors for some specific maneuvering applications, however, they are not designed to identify whether the valid drivers are in terms of security applications, which can prevent the car theft problem.

C. System Overview

To achieve the proposed goal, we present a framework of capturing and modeling dynamic human driving behaviors. By learning from the driving performances, individual dynamic model is obtained, which is utilized as the classifiers to identify the drivers.

Firstly we design experimental platform introduced in Section II. a real-time graphic simulator namely the experimental platform which offers the full controls including steering as well as the brake and gas pedals is described.

Further we collect the human driving data directly for HMM training, which includes steering, acceleration and braking only. We do not utilize other car dynamics and environmental variables as the inputs, such as the car's yaw angle with respect to the road, lateral offset to the road's center, the road curvature, etc, which benefits the efficiency and robustness of the system. To capture aforementioned environmental data needs visual sensors, position or velocity sensors, causing difficulties to be implemented on real vehicles.

Then we introduce model to model similarity distance and human to model similarity distance by HMM to measure the human dynamic behaviors. In Section IV, the experimental processes are presented as well as the results.

Lastly we discuss the experimental results which verify that the proposed method is valid and useful against the vehicle thefts problem.

I. Experimental Design

In this section, the technical descriptions of the implemented hardware and software platforms are presented. we design a experimental platform which includes three parts, a real-time graphic simulator offering the full controls including steering as well as the brake and gas pedals, a sensory system with a processor circuit board to capture human driving behavior data and analysis system to model and identify human behavior.

Fig. 1 shows the driving simulation subsystem. In this system, a simulated driving environment which bears substantial resemblance to a comparable real driving task is developed. Although some aspects of a real driving task cannot be modeled well in a simulated driving environment, including driving control reality, variable road conditions, etc, we choose simulated driving task because it embodies the qualities which meet that criterion for comparing and identifying the individual dynamic behavior and also the focus of this thesis is the analysis of human behaviors themselves.

Fig. 1. The simulation hardware.

In the data capturing subsystem, a processor circuit board is utilized to sense and gather the individual driving behavior data from the driving environment simulation subsystem. With the driving control sensing device, 3 channels of analog signals are gathered, which are acceleration, braking, and braking. Those signals are processed by an analog-to-digital converter at the sampling time of 100 ms and then the digitized values are sent to the micro computer (in our experiment ATmega8535L). The received data $X(t)$ can be represented by

$$X(t) \doteq \{a(t), b(t), c(t)\} \tag{1}$$

where $a(t)$ represents the normalized acceleration value, $b(t)$ represents the normalized braking value and $c(t)$ represents the normalized steering value.

In the human behavior analysis subsystem, the HMM introduced in the following section is applied to the data retrieved. For our goal is to distinguish the authorized drivers from others, human behavior model library of each driver is generated from the corresponding input data by machine learning. Once the models are ready, we implement them as the classifier in the system in response to the real time individual driving performance.

We propose to approach driver recognition and similarity evaluation problems by modeling dynamic human behavior as an hidden Markov model (HMM) with its parameters learned from training data. Human driving behaviors associated with individual driver are recognized by evaluating the trained HMM.

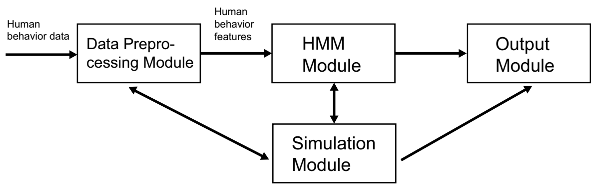


Fig. 2. HMM block diagram of the system for modeling and evaluation.

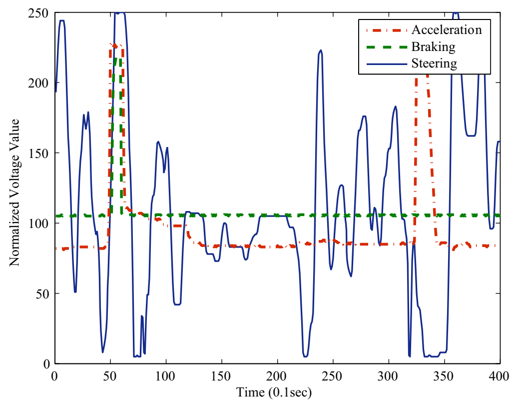


Fig. 3. Human driving behavior data.

In the implementation procedure, as shown in Fig. 2, for each driver, we want to design a separate N-state HMM.

We represent the human driving behavior as a time sequence in Fig. 3 from the previous data sensing and capturing subsystem. For each driver, we have a training sequence consisting of a number of driving data associating the driver. The task is to build individual driver model. This task is done by using the HMM training procedure to optimally estimate HMM model parameters for each driver. Once the set of HMMs has been designed and optimized and thoroughly studied, recognition of an unknown human dynamic behavior is performed to score each behavior model based upon the given test observation sequence, and select the driver's identity whose models core is the highest matched (or have the highest likelihood). The likelihood also can explain the similarity measure of model to model and human to model for evaluation.

II. Modeling and Evaluation via Hidden Markov Model

A. Introduction

In this section, we adopt HMM to account for dynamic behavior modeling and similarity evaluation by modeling dynamic human behavior as an HMM with its parameters learned from training data. For each driver, we want to design a separate N-state HMM. We represent the human driving behavior as a time sequence. We have a training sequence consisting of a number of driving data associating the driver. The task is to build individual driver model. This task is done by using the HMM training procedure to optimally estimate HMM model parameters for each driver. Once the set of HMMs has been designed and optimized and thoroughly studied, recognition of an unknown human dynamic behavior is performed to score each behavior model based upon the given test observation sequence, and select the driver's identity whose models core is the highest matched (or have the highest likelihood [8]). The likelihood also can explain the similarity measures of model to model and human to model for evaluation.

B. Mathematic Description

A hidden Markov model is a collection of finite states connected by transitions. Each state is characterized by two sets of probabilities: a transition probability, and a discrete output probability distribution or continuous output probability density function which, given the state, defines the condition probability of emitting each output symbol from a finite alphabet or continuous random vector.

A HMM can be defined by:

- $\{S\}$ — a set of state including an initial state S_I and a final state S_N
- A — the transition probability matrix, $A = a_{ij}$, where a_{ij} is the transition probability of taking the transition from state i to state j
- B — the output probability matrix, $B = b_j(O_k)$ for discrete HMM or $B = b_j(x)$ for a continuous HMM, where O_k stands for a discrete observation symbol, and x stands for continuous observations of k-dimensional random vectors.

If the initial state distribution $\pi = \{\pi_i\}$, the complete parameter set of the HMM can be expressed compactly as

$$\lambda = \{A, B, \pi\} \tag{2}$$

Given the definition of HMM, there are three basic problems of interest that must be solved for real world applications: the evaluation problem, the decoding problem, and the learning problem. The solutions to these three problems are the Forward-Backward algorithm, the Viterbi algorithm, and the Baum-Welch algorithm[9].

C. Problem Formulation

Having defined the most likely performance, we are able to use HMM to model human driving behaviors. We consider human driving data including steering, acceleration and braking as the observable stochastic process and human knowledge or strategy as the underlying stochastic process. Since the HMM has an ability to absorb the suboptimal characteristics within the model parameters, human intention or strategy for the driving task can be represented by transition possibilities and output possibilities, and using the same model we can "learn" human intention or strategy.

To fix ideas, consider the following procedure for modeling and evaluation of human driving behavior. For each driver, we want to design a separate N-state HMM. We represent the human driving behavior signal of a given driver as a time sequence of coded spectral vectors. We assume that the coding is done using the aforementioned data preprocessing methods; hence each observation is the index of the spectral vector closest (in some spectral sense) to the original human behavior data. Thus, for driver, we have a training sequence consisting of a number of repetitions of sequences of data indices of the driver's skill. The first task is to build individual driver models. This task is done by using the solution to "train" the HMM [9] to optimally estimate model parameters for each driver model. To develop an understanding of the physical meaning of the model states, we use the solution to the decoding problem (Viterbi algorithm [9]) to segment each of the driver training sequences into states, and then study the properties of the spectral vectors that lead to the observations occurring in each state. The goal here would be to make refinements on the model (e.g., more states, different preprocessing methods, etc.) so as to improve its capability of modeling the human dynamic driving behavior sequences. Finally, once the set of HMMs has been designed and optimized and thoroughly studied, recognition of an unknown dynamic driving data is performed using the solution to evaluation problem [9] to score each driver model based upon the given test observation sequence, and select the driver identity whose models core is highest (i.e. the highest likelihood).

Consider a system which can be described at any time as being in one of a set of N distinct states $S_1, S_2, \cdots S_N$, and the states are unobservable. We consider these states corresponding to the human mental states and the output symbols corresponding to his actions. The actual state at time t measured from action is denoted by q_t. When the system is in state $qt = S_i$, M distinct output symbols $O_1, O_2, \cdots O_M$ can be observed.

A discrete output probability distribution, $B = b_i(k)$, is associated with each state, where

$$b_i(k) = P[O_k \;\; at \;\; t \mid q_t = S_i], 1 \leq i \leq N, 1 \leq k \leq M \quad (3)$$

At next time $t+1$, the system goes to state $q_{t+1} = S_j$ with transition probability a_{ji}, where

$$a_{ji} = P\left[q_{t+1} = S_j \mid q_t = S_i\right], 1 \leq i, j \leq N. \quad (4)$$

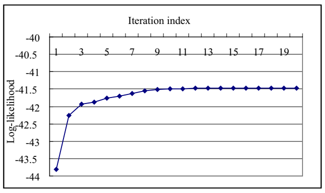
III. Experimental Results

Learning can be done due to the raw data by employing a multi-dimensional HMM. To model the human behavior data $X(t) = \{a(t), b(t), c(t)\}$, a 9 dimensional HMM is employed to encode human skill. We firstly employed FFT technique for preprocessing the 3 dimensional time sequence $X(t)$. The Hamming window was first used with a width of 20 seconds (200 data points) in every 10 seconds. FFT analysis is then performed for every window and the first 3 orders of FFT is kept for further precessing. It means we transfer the original data matrix of size 200×3 to a matrix of size 3×3 each 10 seconds. Then the data is aligned into a single row as a 1×9 vector.

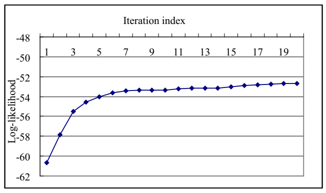
With the retrieved data segments, we employ the Baum-Welch algorithm to learn 2000 of them for the HMMs and employ the Forward-Backward algorithm to evaluate the other 2000 data segments. Firstly the training data is divided as 20 sequences and each sequence contains 100 data segments. Namely each sample point in the training set is a matrix of size 100×9 and for each driver we collet 20 samples for training and other 20 for testing. We train 6 *states* left-right HMMs for all 7 drivers. We initialize all HMMs parameters using a uniform segmentation of each training data sequence. Each sequence is split in 6 consecutive section, where 6 is the number of states in the HMM, the vectors thus associated with each state are used to obtain initial parameters of the sate-conditional distributions.

With these initial parameters, the Forward-Backward algorithm is run recursively on the training data. The Baum-Welch algorithm is used iteratively to reestimate the parameters according to the forward and backward variables. 20 iterations are run for the training processes. The Forward algorithm was used for scoring each trajectory. Fig. 4 shows all 7 HMMs forward scores of the results of the Forward-Backward algorithm, shown as the log-likelihood versus the learning iteration index.

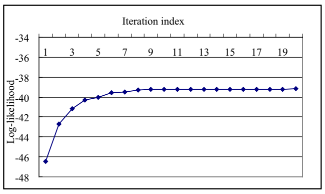
The score increase indicates that the improvement of the model parameters. The parameters converge after about 9 iterations. After the learning iterations, 7 HMMs are retrieved from the learning data samples, as the HMMs from λ_1 to λ_7, representing the human driving behavior models from 7



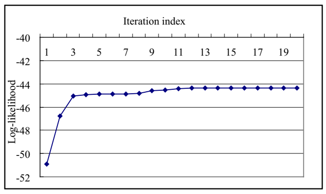
(a) The forwad scores for HMM #1 (Meng)



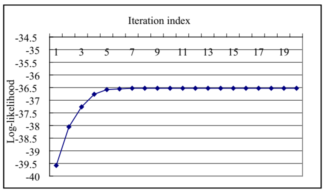
(b) The forwad scores for HMM #2 (Ou)



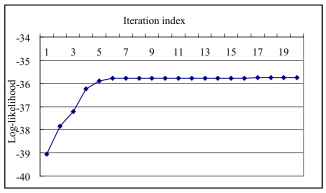
(c) The forwad scores for HMM #3 (Ye)



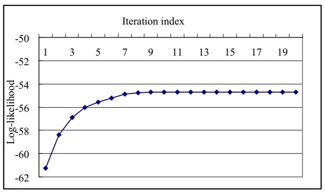
(d) The forwad scores for HMM #4 (Huang)



(e) The forwad scores for HMM #5 (Wang)



(f) The forwad scores for HMM #6 (Wu)



(g) The forwad scores for HMM #7 (Shen)

Fig. 4. Forward learning scores normalized with respect to the sequence length T_i (Log-likelihood-Iteration index) for HMM #1 to #7, which is learnt from the driver data of Meng, Ou, Ye, Huang, Wang, Wu and Shen, with $n = 6$.

human subjects attending the test, who are Meng, Ou, Ye, Huang, Wang, Wu and Shen.

To evaluate the HMMs for recognizing drivers through the corresponding driving behavior sequences, we use the date segments, as the same size as the training samples, from the testing set for drivers identification. For each testing data segment, we derive the log-likelihood values through Forward-Backward algorithm to all trained HMMs and then the maximum log-likelihood is selected. Thus the driver identification is denoted as the corresponding HMM from which the maximum log-likelihood is derived.

We have 2000 testing sample points for each driver in the set which are in the same preprocessing methods and the same size. Each 100 sample points is aligned as the testing data segment in size of 100×9 and totally there are 20 data segments for each driver identification test. The driver identities are counted each round and the final results are shown in Fig. 5. The diagonal marked in grey is the successful identification and the success rates are calculated and shown in Table I.

Also some examples of testing results are shown in Fig. 6.

Count		HMM #1 Meng	HMM #2 Ou	HMM #3 Ye	HMM #4 Huang	HMM #5 Wang	HMM #6 Wu	HMM #7 Shen
Testing data sequences from the corresponding drivers	#1	**19**	1	0	0	0	0	0
	#2	0	**16**	3	0	0	0	1
	#3	7	0	**8**	0	2	3	0
	#4	4	0	1	**14**	0	0	1
	#5	0	0	1	0	**12**	7	0
	#6	0	0	1	0	2	**17**	0
	#7	0	0	0	0	0	0	**20**

Fig. 5. Counts of driver identities due to testing data samples and trained HMMs, with $n = 6$ and size of each simulation sequence is 100×9.

Log-likelihood		HMM #1 Meng	HMM #2 Ou	HMM #3 Ye	HMM #4 Huang	HMM #5 Wang	HMM #6 Wu	HMM #7 Shen
Sample sequences from the testing data segments set	#1	**-4002.4**	-4312.8	-4315.6	-4978.1	-4345.5	-5551.7	-4867.9
		-4012.4	-4305.6	-4291.5	-4733.4	-4345.5	-5355.2	-4930.8
		-4074.2	-4322.7	-4562.7	-4908.3	-4526.6	-5334.3	-4993.1
		-4056.9	-4317.3	-4584.5	-5017.6	-4468.7	-5565.8	-5014.9
	#2	-10274	**-5489.6**	-6260.2	-8646.9	-6509.3	-474190	-5593.8
		-16410	**-5819.2**	-6616.9	-11296	-7522	-1093100	-6088.7
		-13218	**-5579.5**	-6607	-9394	-7015.4	-335760	-5748
	#3	-4837.2	-4731	**-4776.9**	-5437.2	-5478.5	-6014	-5451.9
		-4420	-4639.7	**-4694.8**	-4825.8	-4939.8	-5468.5	-5468.3
	#4	-4066.5	-4409.8	-4499.9	**-4079.1**	-4451.4	-5091.7	-5038.5
		-5640	-5267.3	-5553.7	**-5030.8**	-6122.4	-28307	-5552.1
		-4359.2	-4588.4	-4497.1	**-4324.6**	-5410.7	-4495.2	-5245.8
	#5	-3872.4	-3843.1	-3838.2	-3636.8	**-3278.2**	-4061.2	-4686.3
		-3980.2	-3925.1	-3911.5	-3885.4	**-3576.3**	-4325.8	-4718
	#6	-4436.2	-4214.2	-3813.8	-4585.4	-4442.9	**-3405.6**	-4861.9
		-4190.5	-4114.6	-3638	-4575.5	-3948.2	**-3195.1**	-4762.9
	#7	-6780.2	-6138.9	-6544	-6912.2	-6436.5	-57602	**-5291.7**
		-10624	-6068.7	-6497.9	-13619	-7045.5	-206660	**-5191.7**

Fig. 6. Log-likelihood of sequences from testing samples set to the trained HMMs, with $n = 6$ and size of each simulation sequences is 100×9.

σ		HMM #1 Meng	HMM #2 Ou	HMM #3 Ye	HMM #4 Huang	HMM #5 Wang	HMM #6 Wu	HMM #7 Shen
Sample sequences from the testing data segments set	#1	**0.780**	1.726	1.739	9.470	1.877	41.083	7.143
		0.800	1.695	1.635	5.063	1.877	24.850	8.390
		0.938	1.771	3.272	7.921	2.983	23.557	9.840
		0.897	1.746	3.459	10.477	2.572	42.593	10.405
	#2	8.783E+04	**0.424**	3.047	1.367E+03	5.763	∞	0.554
		5.774E+11	**0.986**	7.590	1.200E+06	76.893	∞	1.965
		1.640E+08	**0.534**	7.400	9.245E+03	21.038	∞	0.822
	#3	8.887	6.773	**7.617**	41.252	45.849	180.440	42.833
		3.056	5.362	**6.174**	8.632	11.555	44.691	44.668
	#4	1.540	3.707	4.668	**1.591**	4.123	21.216	18.516
		86.276	33.249	69.183	**18.155**	296.407	1.323E+27	68.900
		3.257	5.854	4.634	**2.981**	47.986	4.612	31.469
	#5	1.982	1.839	1.816	1.085	**0.433**	3.213	15.902
		2.611	2.268	2.191	2.049	**0.929**	6.323	17.245
	#6	19.369	10.976	3.941	28.372	19.704	**1.387**	57.559
		10.330	8.507	2.513	27.662	5.558	**0.809**	44.680
	#7	13.932	2.701	7.613	19.528	5.782	4.099E+57	**0.309**
		2.599E+05	2.257	6.766	5.529E+08	27.465	1.709E+223	**0.239**

Fig. 7. The similarity distance of simulated sequences from the learnt HMMs to the corresponding HMMs, with $n = 6$ and size of each simulation sequences is 20×9.

TABLE I

THE SUCCESS RATES ON CLASSIFICATION RESULTS

Meng	Ou	Ye	Huang	Wang	Wu	Shen
95.0%	80.0%	40.0%	70.0%	60.0%	85.0%	100.0%

4 out of 20 segments from the testing data set of Meng, 3 of Ou, 2 of Ye, 3 of Huang, 2 of Wang, 2 of Wu and 2 of Shen, totally 18 data segments from testing sample set are randomly selected and their log-likelihoods values derived by all trained HMMs from λ_1 to λ_7 are shown. In each row, the maximum log-likelihood value is denoted and the successful identifications are marked in the grey and fault ones are marked in dark red. Three fault identifications occur, one of the data from Ye is recognized as driver of Ou and one of Ye is recognized as Meng, another data from Huang is recognized as Meng.

We define the human-to-model similarity distance here. Assume that we wish to compare data sequence O_i representing the driving behavior of driver i and one HMM λ_j. $\hat{O}_i$ is the simulated observation sequence generated from trained λ_i and O_i is as the same size in dimension of p as $\hat{O}_i$.

Derive the log-likelihood $P(O_i|\lambda_j)$ and $P(\hat{O}_i|\lambda_j)$ using Forward-Backward algorithm for O_i and $\hat{O}_i$ to λ_j, and we have the similarity distance measure σ from O_i to λ_j defined as follows:

$$\sigma_{O_i-to-\lambda_j} = 10^{(P(\hat{O}_i|\lambda_j)-P(O_i|\lambda_j))/p} \quad (5)$$

With this definition, we denote the human to model similarity distance measure in Fig. 7. Fig. 8 to Fig. 14 show the human to model similarity distance measure based on λ_1 (HMM #1 for Meng) to λ_7 (HMM #7 for Shen).

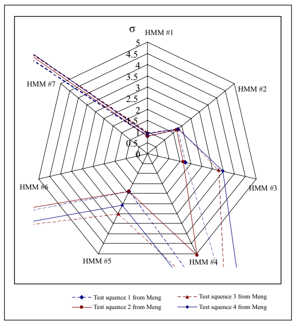


Fig. 8. Similarity distance of testing data to Meng's HMM.

IV. Conclusion and Discussion

This paper has addressed an intelligent vehicle security system towards the solving of vehicle thefts problem. By capturing and analyzing human driving behaviors, unauthorized drivers can be recognized while driving illegally and alarm can be delivered. The advantage of the proposed methodology lies in the fact that the dynamic biometrical features involved

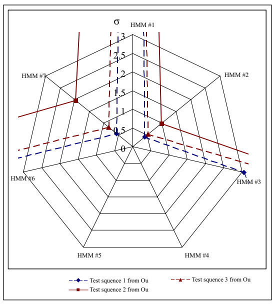


Fig. 9. Similarity distance of testing data to Ou's HMM.

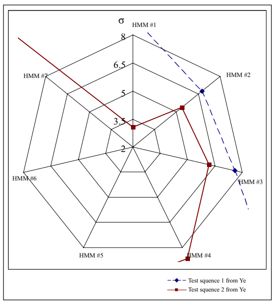


Fig. 10. Similarity distance of testing data to Ye's HMM.

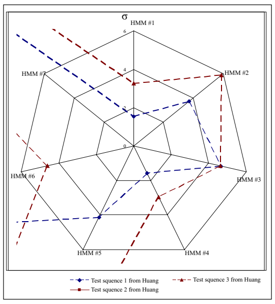


Fig. 11. Similarity distance of testing data to Huang's HMM.

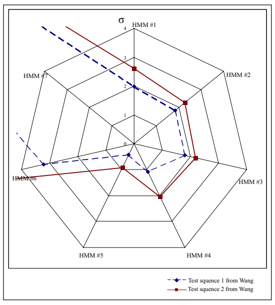


Fig. 12. Similarity distance of testing data to Wang's HMM.

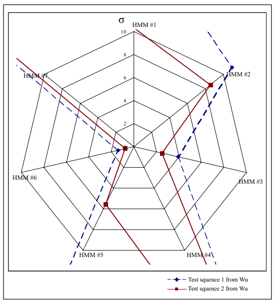


Fig. 13. Similarity distance of testing data to Wu's HMM.

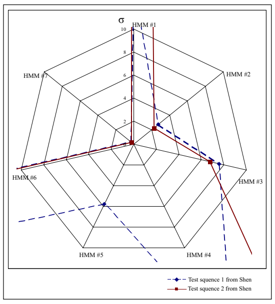


Fig. 14. Similarity distance of testing data to Shen's HMM.

in human driving behavior are unique and more secure than static features.

In this paper, we have built an experimental system for capturing and analyzing human driving behaviors in a simulated driving environment. Data is collected from several testing subjects and then processed through hidden Markov model (HMM) for training human behavior models. Finally, experiments for evaluating the performance of the proposed system are conducted and the results verify that the proposed method is valid and useful against the vehicle thefts problem with a success rate of around 80%.

In the future, more experiments will be conducted on potential user groups to collect and establish a wide human driving behavior library for more precise system and wider applications.

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