Proceedings of the 2008 IEEE International Conference on
Vehicular Electronics and Safety
Columbus, OH, USA. September 22-24, 2008

Driver Behavior Analysis and Route Recognition by Hidden Markov Models

Amardeep Sathyanarayana, Pınar Boyraz, John H.L. Hansen

Abstract— **In this investigation, driver behavior signals are modeled using Hidden Markov Models (HMM) in two different and complementary approaches. The first approach considers isolated maneuver recognition with model concatenation to construct a generic route (bottom-to-top), whereas the second approach models the entire route as a 'phrase' and refines the HMM to discover maneuvers and parses the route using finer discovered maneuvers (top-to-bottom). By applying these two approaches, a hierarchical framework to model driver behavior signals is proposed. It is believed that using the proposed approach, driver identification and distraction detection problems can be addressed in a more systematic and mathematically sound manner. We believe that this framework and the initial results will encourage more investigations into driver behavior signal analysis and related safety systems employing a partitioned sub-module strategy.**

INTRODUCTION

Active safety is seen as the viable solution necessary to reduce vehicle accidents. This approach addresses the problem using system engineering methodology by incorporating all technological solutions related to vehicle, road structure, traffic management and driver assistance/monitoring systems. Vehicle, driver and environment are perceived as the three main components of the system. There is a wide range of systems developed to increase safety of vehicles themselves by making them more stable and reliable. However, a large portion of uncertainty exists in any driving scenario because of the long term as well as instantaneous ability of the driver, changing environment and their interaction. Therefore, the complete solution for reduction of road accidents is only possible by making the vehicles 'aware' of the driving context (environment, route and maneuver type) and the driver status (distracted, neutral, aggressive, drowsy etc.). This can be achieved by analyzing driver behavior signals including driver inputs (i.e., steering wheel angle, steering velocity, brake/gas pedal pressures), vehicle responses to driver inputs (i.e., vehicle speed, acceleration and position), and driver biometric signals (i.e., eye gaze, eye closure, heart rate).

Manuscript received May 15, 2008. This work was supported in part by the NEDO, Japan and UTDallas, USA.

A.S. Author is a graduate student in the Electrical Engineering Department, UTDallas. (axs063000@utdallas.edu)

P. B. Author is with Electrical Engineering Department of UTDallas. (pinar.boyraz@utdallas.edu)

J.H.L.H Author is with the Electrical Engineering Department of UTDallas. (john.hansen@utdallas.edu)

Driver behavior analysis is an interdisciplinary research field where exploratory statistics, stochastic modeling, signal processing, control theory, human factors and artificial intelligence methods are used by researchers to model certain aspects of driver behavior in a mathematical scheme. One emerging trend has been to borrow techniques based on Hidden Markov Models (HMM) from the speech processing and language technology field and apply this to driver behavior modeling for route recognition, driver identification, and distraction detection in an analogy with speech recognition, speaker identification, and stress detection in speech. HMMs which have already been established in speech processing, and are applied in several pattern recognition areas such as place learning and recognition for mobile robots [1], signature recognition [2] and human action learning (intent and skills) for tele-operation of robots [3]. In order to represent both the stochastic and dynamic-continuous properties of human behavior in driving, dynamic models using Kalman filters to estimate the vehicle outputs from driver inputs are employed by feeding their prediction errors into HMMs. Benefits of using HMMs with a dynamical scheme to predict the driver actions within the first 2 sec of an action sequence have been shown in [4]. Driving events were recognized by HMMs in [5] with a recognition rate of 93.8% using only vehicle speed and acceleration as raw data. Following this work, a bottom to top approach drawing an analogy from speech systems was suggested in [6]. Using only steering wheel angle, headway, speed and acceleration values they were able to model most of the maneuvers, discovering the construction sub-units of maneuvers, so called '*drivemes*'. In addition to these encouraging results, HMMs proved to be an efficient method even in complex intersection scenarios. In [7], a single HMM was used to identify the vehicles in conflict with other vehicles in a limited intersection route with appropriate measurements of dynamics of ego-vehicle and surrounding vehicles. This represents the opposite approach in driver behavior signal modeling as it starts from the top (the route) with a single HMM, and parses down the individual meaningful parts (i.e., maneuvers, states) clustering and separating the initial HMM structure. As a result of this approach, they identified three main clusters to represent the driver behavior in intersections, contributing to the understanding of driver behaviors. Moreover, the level of skill or performance of the driver can also be assessed by an HMM incorporating an ANN or similar classification tool to help capture the dynamics of the signals. In [8], recognition

Authorized licensed use limited to: Univ Complutense de Madrid. Downloaded on November 26, 2009 at 19:23 from IEEE Xplore. Restrictions apply.

and performance assessment were proposed together, suggesting a sandwich model of HMM having the additional transition probabilities defined between good and bad performance sequences. In summary, these studies with their reported results are encouraging and serve as a motivation to investigate the capability of an HMM framework in driving behavior modeling. In fact, HMM is a naturally suitable tool to model driver behavior for the following reasons:

- HMMs can model the stochastic nature of the driving behavior, providing sufficient statistical smoothing while offering effective temporal modeling,
- The variations in the driving signals across the drivers can be modeled (driver identification) or suppressed (driver-independent route models) according to the requirements of the desired task.

In this study, an HMM framework will be employed in both a top-to-bottom (TtB) and bottom-to-top (BtT) approach to find the best integrated architecture for modeling driving behavior. First, the proposed formal framework of our approach will be presented in Section I, explaining the use of HMMs for route recognition to capture the dynamics for assessment of the driving situation and driver status. The architecture suggested here attempts to answer two important questions in the driver behavior signal analysis area: maneuver/ route recognition (driver independent, generic model) and driver status assessment (route independent, context-based). Next, the data collection vehicle and experimental procedures will be introduced in Section II, giving details concerning the raw real world data to be used in training the HMM framework. In Section III, the result from route recognition experiments will be given. Finally, a summary and conclusions are drawn in Section IV with discussion for further studies included.

I. FRAMEWORK FOR ANALYSIS OF DRIVING SIGNALS

We propose a framework for recognizing routes supporting a driver behavior analysis system. For the route recognition part, two main stream approaches are used. In order to understand these approaches, we first consider the analogy between a speech recognition and route recognition system hierarchy as given in Figure 1. In addition to this, two mainstream approaches are depicted to support the argument. In the bottom-to-top (BtT) approach, an isolated sub-unit is the focal interest of the overall recognition algorithm. The parallel task within the speech processing/ recognition field is known as phoneme recognition or isolated word recognition. In an analogy similar to isolated word recognition, the maneuvers are intuitively the smallest meaningful parts of the driving task; therefore, isolated maneuver recognition is the main goal in BtT approach. After obtaining a separate HMM for each maneuver defined in the route, the route model can be constructed by an internal semantics and syntax structure. According to this

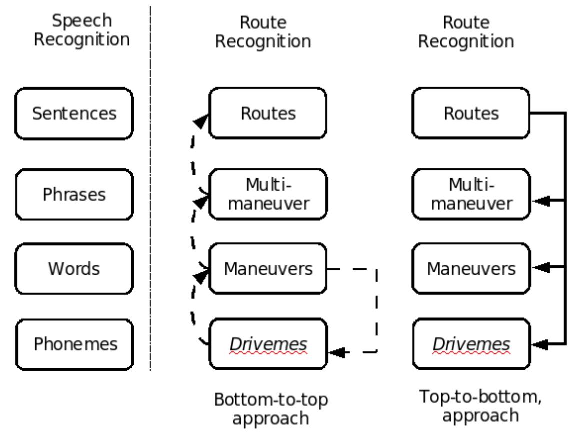

Fig. 1. Hierarchy among the units of speech recognition and route

approach, *drivemes* common to all maneuvers can be discovered and be used to build up maneuver models. These maneuver models can be used to build multi-maneuver models and finally complete routes. This proposed hierarchy approach can be seen schematically in Figure 2.

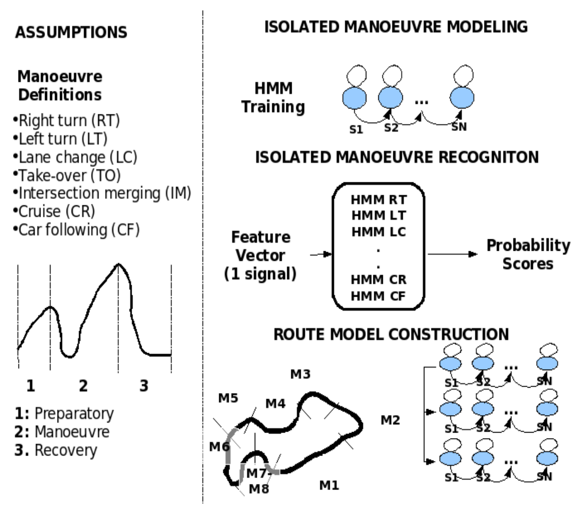

Fig. 2. Bottom-to-top (BtT) approach for route model construction

Alternatively, in top-to-bottom (TtB) approach, a single HMM with a large number of states is trained. In this manner, we assume that there is no *apriori* information known about the individual maneuvers. We assume that we have a record of a meaningful data sequence which is constructed by some units; however, we do not insert restrictions on their duration. After training this HMM framework, certain pruning techniques including clustering and the Viterbi algorithm will be used to determine which states are dominant in the single HMM, while a portion of the route known as a certain maneuver is presented as an observation sequence. The discovered dominant states can be concatenated (state-tying) to represent certain maneuvers, therefore a finer model of the HMM can be obtained for the route. This method is presented schematically in Figure 3.

Authorized licensed use limited to: Univ Complutense de Madrid. Downloaded on November 26, 2009 at 19:23 from IEEE Xplore. Restrictions apply.

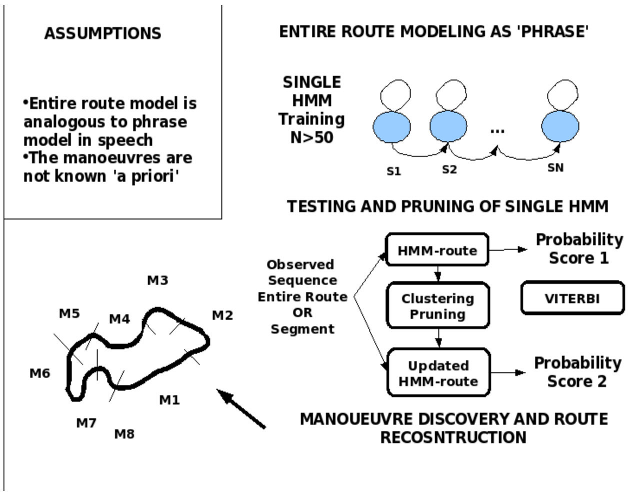

Fig. 3. Top-to-bottom (TtB) approach for route model construction

The aim of both approaches (BtT and TtB) is the same: to obtain a driver independent model of the maneuvers and the route as a reference generic model. As such, the model must be able to average the individual traits of the drivers and adequately represent the overall route and maneuvers. This reference model then can be used to assess the deviation of individual drivers from the 'nominal' path of performing the overall driving task. The route will be completed under both neutral and distracted conditions; therefore, each approach will be applied to these two data sets individually, with the resulting HMM structures to be compared.

The secondary outcome of this study is that while the TtB recognition scheme is examined, it is essentially an exploratory methodology to discover the individual states and maneuvers which are constructed with the overall higher dimensionality HMM. The BtT approach is a complimentary method that assumes that the HMM models of the individual maneuvers can be constructed and used as building blocks to form overall route models. Therefore, these two approaches establish hierarchical model of driving behavior. We believe that this framework will eventually allow us to provide a systematic tool for:

- Driver identification: by measuring the deviations of each driver from the reference route model under neutral driving conditions.
- Distraction detection: by measuring the difference between the models obtained using neutral and distracted driving sessions.

A. Hidden Markov Models

The foundation of HMM is a stochastic Markov process consisting of a number of states with corresponding transitions. At discrete time intervals, the Markov process moves from one state to another according to a set of transition probabilities. State changes in the Markov process are hidden from the user.

HMMs can be characterised by:

- A set of distinct states $S=\{S_i\}$ with q_t denoting a state at time t, with number N
- The initial state distribution $\Pi=\{\Pi_i\}$
- The state transition probability distribution $A=\{a_{ij}\}$
- Each state can produce one of M distinct observation symbols from the set $V=\{V_i\}$
- The observation probability distribution function in state j, B_j

Therefore, HMMs can be written in the form of a vector $\lambda=\{N,M,A,B,\ \Pi\}$. In continuous density HMMs, the emission probability values are represented with a distribution profile usually Gaussian Mixtures. An extensive explanation of how HMMs work can be found in [9, 10]. In this investigation both DHMM and CDHMM are used.

II. DATA COLLECTION VEHICLE AND PROCEDURE

The raw data used in this investigation represents a small portion of the UTDrive Corpus collected during 2006-2007. The corpus is formed by the data collected from real-road experiments using UTDrive Vehicle converted from a Toyota RAV4 vehicle (Figure 4).

Fig. 4. Top-to-bottom (TtB) approach for route model construction

The vehicle (Figure 4) is equipped to perform multi-modal data collection with signal channels including:

- Videos: driver and the road
- Microphone array and close microphone to record driver speech
- Distance sensor using laser
- GPS for position measurement
- CAN-Bus: vehicle speed, steering wheel angle, brake/gas
- Gas/Brake pedal pressure sensors

Authorized licensed use limited to: Univ Complutense de Madrid. Downloaded on November 26, 2009 at 19:23 from IEEE Xplore. Restrictions apply.

The driving scenarios include two different routes: residential and commercial areas including right turn, left turn, lane change, cruise and car following segments. Each route is driven by each driver twice: neutral and distracted.

In this present investigation, only CAN-Bus signals are used since they are readily available in the vehicle and offer a low-cost solution for vehicle/driver modeling. However, in further studies, other sensors will be fused to obtain more comprehensive results. The CAN-Bus signals used are: vehicle speed, steering wheel angle, brake/ acceleration pedal counts, which are all shown in their raw format in Figure 5.

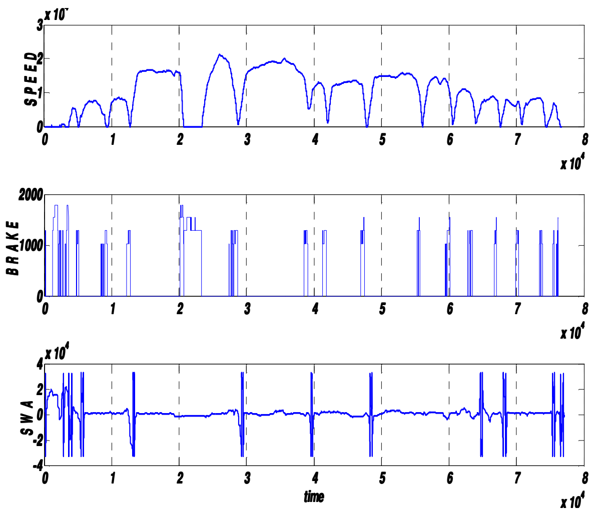

Fig. 5. Sample CAN-Bus signals: Speed, steering wheel angle and break value

III. ROUTE RECOGNITION RESULTS

A. *Bottom-to-Top Approach: Individual Maneuvers*

In BtT approach, for recognition of the individual maneuvers, DHMM and CDHMM are employed. For the sake of simplicity only left turn (LT), right turn (RT) and lane change maneuvers are considered. The HMM framework has two steps for the driver behavior analysis: Maneuver recognition and distraction detection. This way the system can predict the type of maneuver first and can have pro-active safety measures by activating some specific controllers in the vehicle suitable for the particular type of maneuver and the context of the traffic at that moment.

Intuitively, the individual maneuvers are considered to be having four states: perception, preparation, maneuver and recovery. The data were segmented on 2-sec and 5-sec basis and each segment had a feature vector containing: raw signals of speed, steering wheel angle, brake values, the deltas of these signals, standard deviation of steering wheel angle and time on task for each maneuver. Eight drivers' data were used in round-robin training way leaving one driver's data out each time. For CDHMM training, 8, 16, 32 and 64 Gaussian mixtures were tried. The best results of maneuver recognition are obtained with 64 mixtures, 4 state CDHMM as shown in Table I. The values represent the percentage of the data correctly recognized. Next to percentages, in parentheses the total number of that maneuver and the number of correctly recognized ones are given. From this table it can be seen that in overall there are 112 right turns, 29 left turns, and 70 lane change events with 100%, 93%, and 81% respectively recognized correctly. These rates are very encouraging, suggesting we can proceed to detect if the particular maneuver contains distraction or if it is neutral. The results of distraction detection can be seen in Table II.

TABLE I
INDIVIDUAL MANEUVER RECOGNITION BY CDHMM

Driver		LT	RT	LC
1	LT	100 (2/2)	0	0
	RT	0	100 (14/14)	0
	LC	0	0	100 (8/8)
2	LT	85.71 (6/7)	14.29 (1/7)	0
	RT	0	100 (14/14)	0
	LC	0	14.29 (1/7)	85.71 (6/7)
3	LT	100 (2/2)	0	0
	RT	0	100 (14/14)	0
	LC	8.33 (1/12)	25 (3/12)	66.67 (8/12)
4	LT	100 (7/7)	0	0
	RT	0	100 (14/14)	0
	LC	11.11 (1/9)	11.11 (1/9)	77.78 (7/9)
5	LT	100 (2/2)	0	0
	RT	0	100 (14/14)	0
	LC	0	0	100 (10/10)
6	LT	50 (1/2)	50 (1/2)	0
	RT	0	100 (14/14)	0
	LC	14.29 (1/7)	14.29 (1/7)	71.43 (5/7)
7	LT	100 (5/5)	0	0
	RT	0	100 (14/14)	0
	LC	0	22.22 (2/9)	77.78 (7/9)
8	LT	100 (2/2)	0	0
	RT	0	100 (14/14)	0
	LC	0	25 (2/8)	75 (6/8)

TABLE II
DISTRACTION DETECTION BY CDHMM

Driver	LT		RT		LC	
	N	D	N	D	N	D
1	0/1	1/1	6/7	2/7	0/2	6/6
2	0/6	1/1	2/7	3/7	0/2	5/5
3	0/1	1/1	4/7	3/7	0/3	9/9
4	1/6	1/1	5/7	3/7	0/3	6/6
5	1/1	1/1	3/7	4/7	0/2	8/8
6	1/1	1/1	4/7	3/7	0/1	6/6
7	0/1	3/4	3/7	2/7	0/2	7/7
8	0/1	1/1	5/7	3/7	0/1	7/7

N: neutral, D: distracted

The distracted drivers were recognized with 100% rate for LT and LC maneuvers; however the HMMs used for distraction detection for RT does not have the same performance. It can be argued that the maneuver samples

Authorized licensed use limited to: Univ Complutense de Madrid. Downloaded on November 26, 2009 at 19:23 from IEEE Xplore. Restrictions apply.

taken from an experiment with distractions do not necessarily reflect the distraction; some of them might be close to neutral. In addition to this, the system is capable of detecting the distraction; however, it is still prone to false alarms. The same time frames and feature vectors are used to train DHMMs as well. K-means algorithm is used for vector quantization of the data. Code-book sizes of 4, 8 and 12 are used to quantize the feature vectors for symbol representation. When 4 symbols and 4 states are used for DHMM, the overall recognition rates for maneuvers are 85%, 62% and 50% for right turn, lane change and left turn respectively. When the codebook size is increased to 12 the performance of DHMMs are increased as expected. The improved recognition rates are 100%, 87% and 75% for RT, LC and LT. The distraction detection rate in a correctly recognized maneuver was found 95%, a sample result of distraction detection for RT is given in Fig 6. It should be also noted that as we increased the number of maneuvers in our database a significant improvement in recognition rate was recorded. As an example of how these results are obtained Fig 7 shows the likelihood scores of DHMMs trained using LC maneuvers in round-robin process and their response to test data containing RT, LT and LC. Similar patterns are obtained with DHMMs trained for LC and LT, thus, the corresponding DHMM trained for that maneuver gives the highest values for the test signal with the same characteristics. Hence using a maximum-likelihood classification algorithm the maneuver can be recognized.

We also performed tests by reducing the sequence length fed to DHMM, it was still possible to correctly recognize the maneuver with only 20% of the whole length of the maneuver. This result implies that a recognition system based on DHMMs can be a base for a predictive active safety system to recognize the maneuver well before the critical parts and can prepare the pro-active controllers in the vehicle on time.

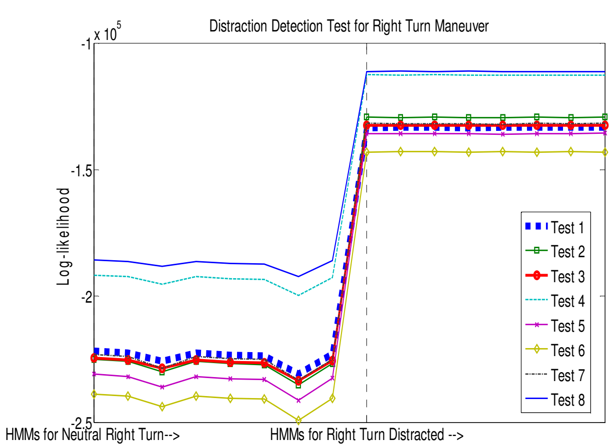

Fig.6. Sample distraction detection results for RT maneuver

If we compare the performances of DHMM and CDHMM systems, the recognition of maneuvers can be done with CDHMM; however, the distraction detection part would lead to false alarms. On the contrast, DHMM gives lower performance in recognition; however, can assure there are limited false alarms. Using these results, a system with the CDHMMs in the first part to recognize the maneuver and a DHMM in the second part to detect the distraction would give the best combination in terms of overall performance.

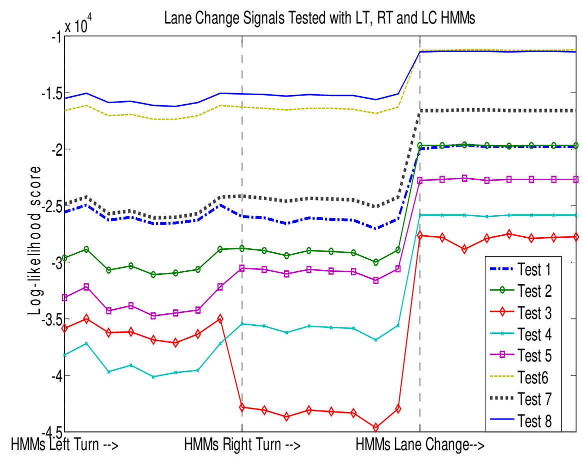

Fig.7. Sample maneuver recognition for LC

B. Top-to-Bottom Approach for Route Recognition

In TtB approach, we assumed that the maneuvers are not defined and resultant DHMM represented the whole route with 20 states using 8 symbols for the codebook. The training curve for this DHMM can be seen in Figure 8.

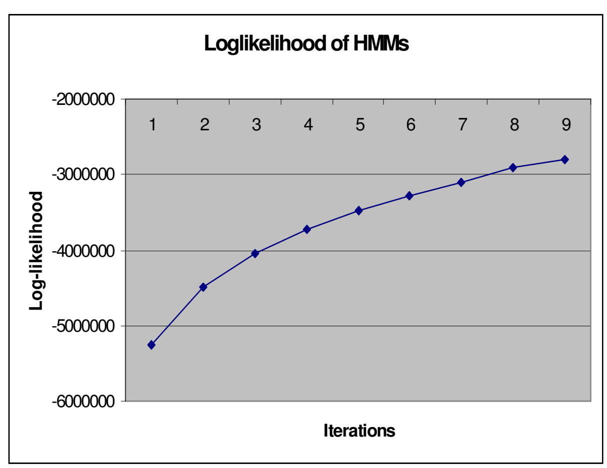

Fig.8. HMMs with 20 states and 8 symbols converging to a rough model for whole route

After training stage, the DHMM is used to identify the dominant states for each maneuver using Viterbi algorithm.

Authorized licensed use limited to: Univ Complutense de Madrid. Downloaded on November 26, 2009 at 19:23 from IEEE Xplore. Restrictions apply.

A sample result for Right Turn (RT) maneuvers is shown in Fig. 9. As can be seen from Fig 9, RT maneuver dominantly have min 2, max 5 states. The dominant states are discovered for LT and LC as well and given in Table III. From the results of TtB approach we can conclude that intuitively selected four states in BtT approach to represent each maneuver was a reasonable choice. Therefore, we can carry on constructing different maneuver models with this methodology discovering the number of dominant states for each.

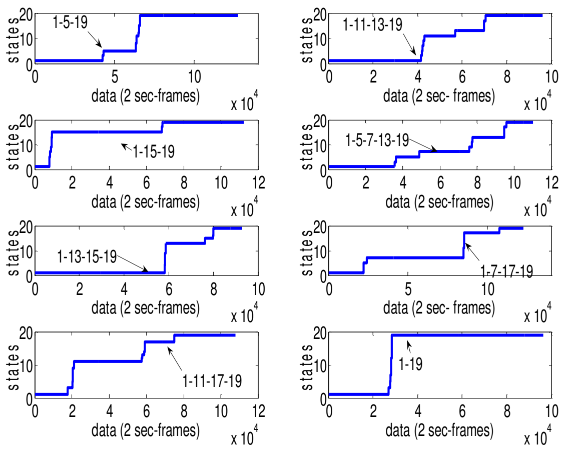

Fig.9. Sample RT maneuvers from 8 drivers: state discovery by Viterbi algorithm

TABLE III
DOMINANT STATE DISCOVERY BY VITERBI

Driver	Left Turn	Lane Change
1	2-6-18	2-8-16-18
2	2-14-18	2-5-16-18
3	2-12-18	2-5-8-10-18
4	2-8-18	2-8-18
5	2-10-18	2-5-8-16-18
6	2-10-18	2-5-18
7	2-10-18	2-18
8	2-10-18	2-12-18

IV. CONCLUSIONS

In this investigation, using only three CAN-Bus signals (i.e., vehicle speed, steering wheel angle and brake force) three different maneuvers (left turn, right turn and lane change) were recognized. Hidden Markov Models were employed in bottom-to-top (BtT) and top-to-bottom (TtB) approaches in a complimentary way; latter being used to discover the optimum number of states for each maneuver verifying the intuitive BtT method. The study contributes to driver behaviour signal processing area in two ways. First, it proposes a hierarchical way of formulating the maneuvers and combining them for the route models. Second, it proposes a plausible solution to maneuver recognition and driver distraction detection problems. We believe that this study will open the ways to construct systems analyzing driver behaviour based on time windows as small as 2 seconds. There is also possibility of using such a system to activate certain controllers in a safer way in intelligent vehicles provided that this system's output (maneuver context and distraction) is used for decision making.

REFERENCES

[1] O. Aycard, F. Charpillet, D. Foht and J.F. Mari, "Place learning and recognition using hidden Markov models" in *Proc, IEEE Int. Robots Syst., 1997,* Grenoble, France, pp. 1741-1746.

[2] L.Yang, , B.K. Widjaja and R. Prasad, "Application of hidden Markov models for signature verification", *Pattern Recognition,* vol. 28, pp. 161-169, Feb. 1995.

[3] J. Yang, Y. Xu, "Human Action Learning via Hidden Markov Model", *IEEE Trans. Syst. Man and Cyber.-Part A: Syst. And Humans,* vol. 27, No. 1, Jan. 1997.

[4] A. Pentland, A. Liu, "Modeling and Prediction of Human Behavior", *Neural Computation,* vol. 11, pp. 229-242, 1999.

[5] D. Mitrovic, "Reliable Method for Events Recognition", *IEEE Trans. on Intelligent Transp. Syst.,* vol. 6, no. 2, pp. 198-205, June, 2005.

[6] K. Torkkola, S. Venkatesan, H. Liu, "Sensor Sequence Modeling for Driving", FLAIRS Conference, pp. 721-727, Clearwater Beach, Florida, USA, , 2005. [online source: DBLP, http://dblp.uni-trier.de]

[7] X. Zou, "Modeling Intersection Driving Behaviors: A Hidden Markov Model Approach-I", *Jrnl. of Transportation Res. Board,* pp.16-23, 2006.

[8] P. Boyraz, M. Acar, D.Kerr, "Signal Modelling and Hidden Markov Models for Driving Manoeuvre Recognition and Driver Fault Diagnosis in an urban road scenario", *Proc. Of IEEE IVS'07,* pp. 987-992, Istanbul, Turkey, 13-15 June, 2007

[9] L.R. Rabiner, "A Tutorial on hidden Markov models and selected applications in speech recognition", *Proc. IEEE,* vol. 77, Issue 2, Feb 1989, pp. 48-61.

[10] J.R. Deller, J.H.L. Hansen, G. Proakis, Discrete Time Processing of Speech Signal, IEEE Press Classic Reissue, Hardcover, 21 Sept 1999.

Authorized licensed use limited to: Univ Complutense de Madrid. Downloaded on November 26, 2009 at 19:23 from IEEE Xplore. Restrictions apply.