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Signal Modelling and Hidden Markov Models for Driving Manoeuvre Recognition and Driver Fault Diagnosis in an urban road scenario

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Abstract— **Hidden Markov models (HMM) are used to identify a vehicle's manoeuvre sequence and its appropriateness for a given urban road driving situation. One of the novel aspects of this work has been the development of an efficient signal modelling approach to form a context-aware, flexible system which proved to respond well in urban road scenarios, especially in situations where the driver is likely to have an accident due to impaired performance. Another contribution has been to clarify how HMMs can be used not just to recognize vehicle manoeuvres but also to distinguish an impaired driver from a normal one in complex driving contexts. The system has worked well on simulator data and is about to be implemented in the real conditions of an urban trajectory.**

INTRODUCTION

DRIVER assistance and attention monitoring systems are the new focus of active safety research. Attention monitoring during highway driving scenarios is being studied and state-of-the-art methods for analysing data are employed on the data collected during well-designed highway simulations or on real roads. [1,2,3,4] However, few such studies consider systems for the diagnosis of driver faults in urban scenarios, due to difficulties in signal modelling and the complexity of possible manoeuvres. The general approach requires modelling the signals based on piecewise polynomials [5] or Kalman filters [6] and then applying larger sequence modelling using stochastic methods such as Hidden Markov Models (HMM). Although these methods produce a solution scheme for the problem, driver fault diagnosis in an urban scenario is not explored using both theoretical and experimental techniques coupled with sufficient data. Previously proposed signal models indicate a quantitative way to express the actual data in terms of vectors and coefficients; however, they cannot handle the differences amongst the drivers in the data pool.

We believe that the driver manoeuvre recognition task is crucial if driver assistance systems are to be useful in a predictive way. However difficult and complex, if the manoeuvres can be segmented into suitable parts corresponding to the phases of actual driving activity, predicting the sequence of these phases can supply a solution for driver assistance systems, as in previous studies [7]. Furthermore, if a quantitative measure of the driver performance for a particular manoeuvre under examination can be derived, these systems can help to diagnose driver faults in an urban scenario, allowing safety systems to react in time.

In this study, system architecture in terms of signal analysis is proposed and tested with a data base containing twenty drivers. Different signal modelling approaches are explored and a new graphical method based on local minima and maxima is proposed, which takes into account the differences amongst drivers. The signals are segmented automatically into meaningful phases using this model. Then, the phases are recognized and classified by a previously trained Artificial Neural Network (ANN). The classes or phases are transferred into a code book usable in stochastic modelling, namely in training HMMs. After modelling, the whole system is tested with samples of good and bad performances of the same manoeuvre.

Here, we will consider the system design, experimental procedure and results in order and discuss in the concluding section how to extend the work with more sensors and in real driving conditions. The aim is to use sound theory and data analysis methods to find a practical solution. Therefore, the theoretical background in system design is first considered in detail, followed by the experimental and results sections.

I. SYSTEM DESIGN

Before describing the system architecture in parts, the whole system and the signal flow must be understood (Fig. 1). The signals used in this study are the vehicle speed and steering wheel angle (SWA). For the sake of simplicity, only these two signals defining the longitudinal and lateral movement of the car are considered in this preliminary search.

First, the signals are normalized into a [-1, 1] interval for steering wheel angle and a [0, 1] interval for the vehicle speed. The signals are then re-sampled into twenty minute time spans for easier modelling. This normalisation and re-sampling comprises the Pre-process step in Figure 1.

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The second step includes the signal modelling and uses a graphical technique exploiting local minima and maxima of the signals to segment them into meaningful phases of the manoeuvre. Although the graphical model is designed through observation, the phase segmentation is executed automatically by the algorithm.

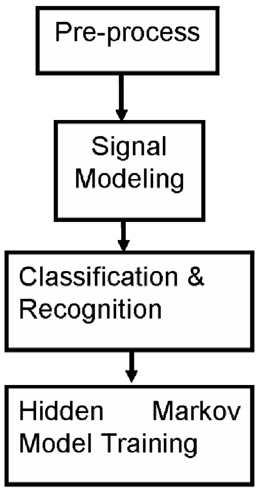

Figure 1. General signal flow and the steps in system design

The third step is the recognition and classification of the manoeuvre phases. For this stage, many recognition schemes could be used. However, due to the large variety in the signals, classification cannot be performed using linear approaches. For this reason ANNs have been employed.

The forth and the final step is to use HMMs to predict the sequences of the signals coded in terms of phases which are labelled by the ANN. The continuous flow of the signal in the system allows autonomous execution which is very important if the system is to be applicable in practice.

A. *Signal Characteristics and Modelling*

For the sake of simplicity, the procedure will be explained using only the 'Right Turn' manoeuvre signal to prove the concept. A well-performed 'Right Turn' and an impaired one can be seen in terms of steering wheel angle in Figure 2 and speed in Figure 3, broken manually into four phases (preparation, manoeuvre and recovery).

A bad and good signal is assessed depending on the ability of driver to keep the lane when he/she is manoeuvring. When the lane deviation was minimum the steering wheel angle and speed signals followed a characteristic pattern as shown with solid lines in Figure 2 and 3.

In the preparation stage the speed should be reduced and the angle must be constant, during the manoeuvre the speed should be kept minimum and the steering angle must be reversed smoothly without jerky movements. If Figure 2 and 3 is looked closely these observations hold for solid lines presenting good manoeuvres and not true for the dashed lines representing the bad performance.

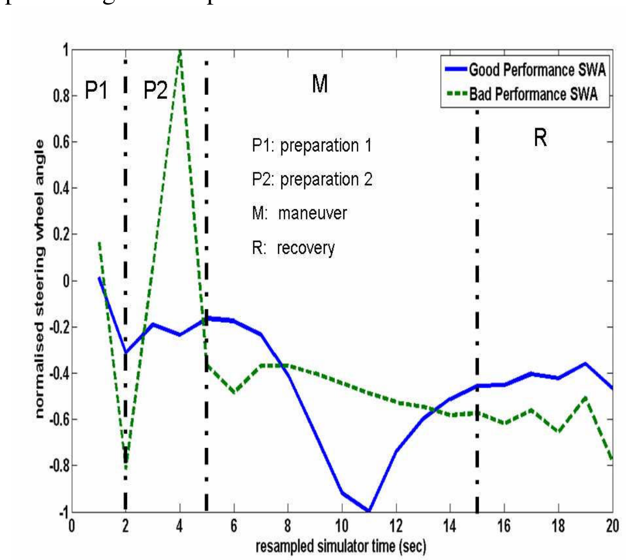

Figure 2. Comparison of a good and bad performance in steering wheel angle signal separated into 4 phases

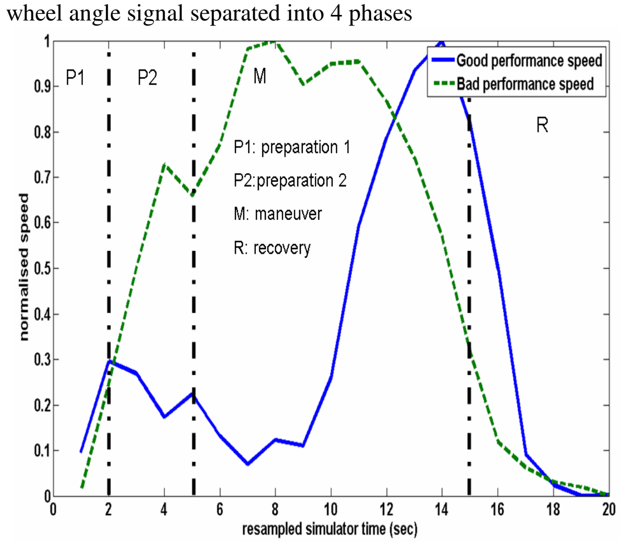

Figure 3. Comparison of a good and bad performance in speed signal separated into 4 phases

The aim of signal modelling is to take the signal characteristics into account and segment the signal into phases automatically. Initially, conventional methods are applied and they indicate a trend in the manoeuvres common to the drivers. Piecewise polynomials are used to examine their potential in segmenting the signals automatically. However, the coefficients and break points as piecewise polynomials do not indicate any method of separation, but help to observe the same trend for the same manoeuvre amongst the drivers studied. (see Figure 4)

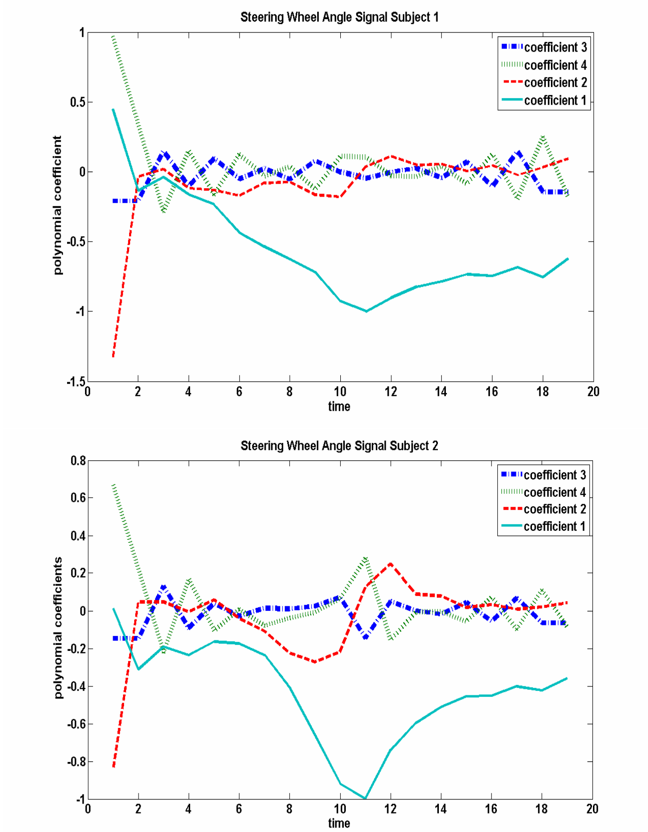

Figure 4. Piece- wise polynomial coefficients for SWA of two driver subjects

For this reason, piecewise polynomials are used to observe the trends and a generic manoeuvre is formed using them to define the shape of the signal in terms of local and global minima and maxima. For the actual segmentation below, rules are derived from the generic signal and used to segment the test signal automatically.

Graphical Segmentation Rules:

- *First two seconds are for initial preparation (P1)*
- *After first 2 sec find the first local maximum: between t=(2-local maximum 1) is preparation phase 2 (P2)*
- *Find the second local maximum after the global minimum: Between t=(local maximum 1-local maximum 2) is manoeuvre phase (M)*
- *Between t=(local maximum 2- 20) is the recovery phase (R)*

The segmented phases for the whole database can be seen in Figure 5 depicting the first and third phases of the 'Right Turn' manoeuvre. This shows the variability of the signal phases within the 'good' performance class. .From this point on the segmented phases database is used rather than the whole signal database. In preparation of this database, the good and bad performance examples are separated as well to test the whole diagnosis system with different cases at the end.

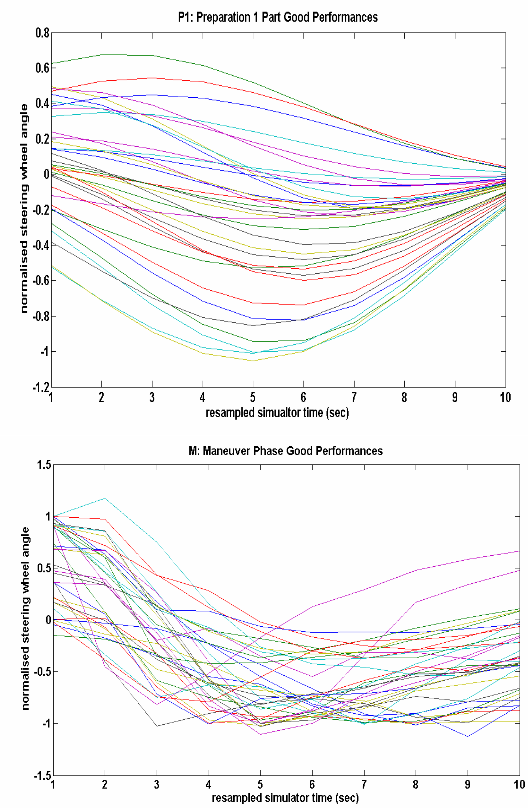

Figure 5. Phase 1 and Phase 3 of the 'Right Turn' manoeuvre showing only the good performances for twenty drivers

B. *Classification and Recognition*

After segmenting the signals into manoeuvre phases, a classification and recognition algorithm is needed to label them. The classification algorithm has two important roles in the whole structure. The first role is to recognize the different phases of the signal when it is coming from a data stream, and the second is to classify them in such a way that the labels of the classification can be used in the next step. In sequence modelling, which comes after classification, a code book representation of the phases is needed and the accuracy of the classification algorithm is very important in getting 'realistic' stochastic models.

The classification algorithm is thus chosen carefully to handle the variation in the common pattern in terms of time shift and magnitude changes. These changes are inherent in such data-driven systems and any algorithm chosen should be able cope with them at an acceptable level, to give correct classification percentages of 95% and higher. Due to variances, time shifts and magnitude distortions of the signals, the classification problem cannot be handled by straightforward linear methods. For this reason an ANN is trained using 35 correctly performed manoeuvre examples. The feed-forward, multilayer perceptron neural network architecture (MLP) is used, with back-propagation error learning. The network contains 3 layers of neurons in a 10-5-1 configuration and uses a Levenberg-Marquard learning algorithm . The training curve of the network can be seen in Figure 6.

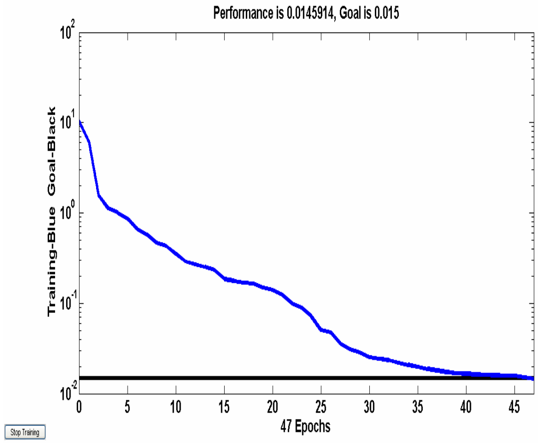

Figure 6. ANN training curve showing the convergence of the training process to performance goal of error=0.015 after 47 training epochs

The trained network is tested with another set of 35 'good' manoeuvres selected randomly from the database and the performance of the network can be observed in Figure 7. The phases of the manoeuvres are assigned to output levels of [1-4] in order and the network is able to classify them correctly. The class number 1 corresponds to preparation phase 1, 2 to preparation phase 2, 3 to manoeuvre and class 4 to recovery phase.

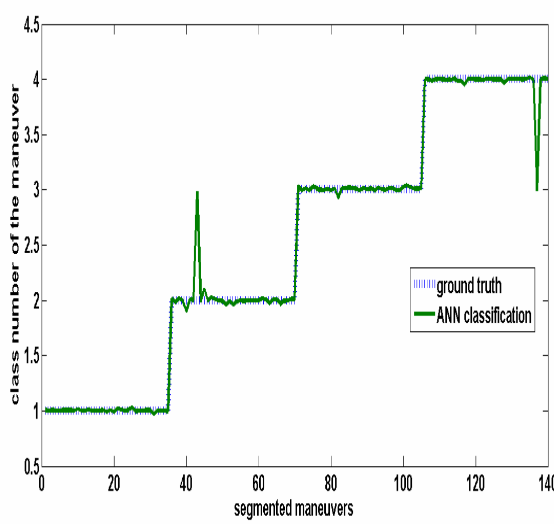

Figure 7. ANN output vs. ground truth signal

A second ANN is trained in the same way to classify bad performance examples of the same manoeuvre, with outputs from 5 to 8, representing the same phases of P1, P2, M and R.

C. Sequence Modelling and Hidden Markov Models

In this section, HMMs are first described briefly before being applied to the particular problem under investigation.

Part1. Theoretical Background

HMMs are probabilistic tools for modelling time series data [8]. The foundation is a stochastic Markov process consisting of a number of states and transition between them. At discrete time intervals, the Markov process moves from one state to another according to a set of probabilities. State changes in the Markov process are hidden from the user.

Discrete 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 $\lambda=\{N,M,A,B,\Pi\}$. There are methods to calculate the probabilities mathematically but they will not be dealt with here. An extensive explanation of how HMMs work can be found in [8, 9].

Part2. Application

A HMM is used here in a bottom-up rather than the top-down approach used in [10]. The top-down approach uses HMM modelling to find 'drivemes', (named after the 'phonemes' used in speech recognition) and employs a hierarchical approach to establish the basic construction units of the manoeuvres. It is an exploratory method. However, we use HMMs in this case to recognize the manoeuvres and the model is built from bottom to top level. The basic construction units are identified by graphical signal modelling and by the ANN, manoeuvres being built using these units.

The sequence of the phases in a certain manoeuvre is considered as a chain of events, which are probabilistically connected. To test our initial system design, the 'Right Turn' manoeuvre is modelled using a code book of length four symbols. These are *Preparation 1, Preparation 2, Actual Manoeuvre,* and *Recovery* coded as a 1 2 3 4 chain having the same labels as the classification algorithm. This chain is nearly deterministic because the states are physically connected and they have to follow each other in a certain manner. Bad performance of the same manoeuvre is coded as 5 6 7 8 chain. The transition between consecutive states is allowed with a transition probability. Additionally, transition between a 'bad' manoeuvre phase and 'good' manoeuvre phase is allowed in the model as long as they are consecutive events. The transition matrix **A** is designed to represent all these possibilities and can be seen in equation (1).

$$A = \begin{bmatrix} 0 & pp & 0 & 0 & 0 & pq & 0 & 0 \\ 0 & 0 & pp & 0 & 0 & 0 & pq & 0 \\ 0 & 0 & 0 & pp & 0 & 0 & 0 & pq \\ pp & 0 & 0 & 0 & pq & 0 & 0 & 0 \\ 0 & qp & 0 & 0 & 0 & qq & 0 & 0 \\ 0 & 0 & qp & 0 & 0 & 0 & qq & 0 \\ 0 & 0 & 0 & qp & 0 & 0 & 0 & qq \\ qp & 0 & 0 & 0 & qq & 0 & 0 & 0 \end{bmatrix} \quad (1)$$

The columns and rows of the transition matrix A represent each state from 1-8: the first half (1-4) representing 'Right Turn' manoeuvre phases in chain form indicating good performance, and second half (5,8) representing the same manoeuvre phases but with bad performance.

pp: probability of transiting into next phase staying in good performance: e.g. A (1,2) : P1(good)→P2(good)

pq: probability of transiting into next phase changing from good to bad performance: e.g. A(1,6) : P1(good)→P2(bad)

qq: probability of transiting into next phase staying in bad performance: e.g. A(5,6): P1(bad)→P2(bad)

qp: probability of transiting into next phase changing from bad to good performance, e.g. A(5,2): P1(bad)→P2(good)

The emission matrix B will be an identity matrix, since the states and observations are the same for our model.

The application of the model to identify real sequences is a reverse engineering approach, which gives insight into development of a quantitative performance measure. The real sequences are used to predict the transition matrix probabilities associated with a particular driver, using a Viterbi algorithm (a method of finding the most likely sequence of hidden states that result in a sequence of observed events). These probabilities are then interpreted as performance index, i.e. a high pp value indicates that a driver tends to stay within the good performance range, whereas a high pq value indicates that the driver tends to change from good to bad performance in successive phases. A higher value of qq means it is more probable that the driver will operate in the bad performance range for a longer time, whereas qp indicates the possibility of shifting to the good performance region. If the probabilities of pq and qp are equal or close enough to each other, the driver has an inconsistent behaviour, which is also considered as bad performance. In the light of this interpretation, a performance value is derived from equation (2), using these identified transition probabilities.

$$P = pp(i=1..4) + qp(i=1..4) + [1 - qq(i=(1..4)] + [1 - pq(i=1..4)]$$
(2)

II. EXPERIMENT

The data were collected during controlled experiments on a range of driver subjects in a vehicle simulator, with several sensors are attached to the system. However, only speed and steering wheel angle signals were utilised for the preliminary research. Twenty subjects with different levels of driving experience participated in the experiment. Therefore, sets of good and bad performance data were obtained for use in building a data driven system and testing it. The urban driving scenario used contained the following events:

- Right Turn/ Left Turn/UTurn
- Roundabout
- Emergency Brake /Reversing

All these events were taken as manoeuvres and subjects were asked to repeat the manoeuvres at least five times.

III. RESULTS

The manoeuvres were modelled and classified as described above and a code book for the HMM was formed. It was observed that the HMM was able to predict the manoeuvres and also was able to give a quantitative measurement of driver performance. In order to visualise different driving performances a 2000 length sequence is simulated with

(i) Good performance [pp=0.9, pq=0.1, qq=0.1, qp=0.9], ***P=3.6***

(ii) Inconsistent performance [pp=qq=pq=qq=0.5], ***P=2***

(iii) Bad performance [pp=0.1, pq=0.9, qq=0.9, qp=0.1], ***P=0.4***

The results of the simulated sequences can be seen in Figures 8, 9 and 10.

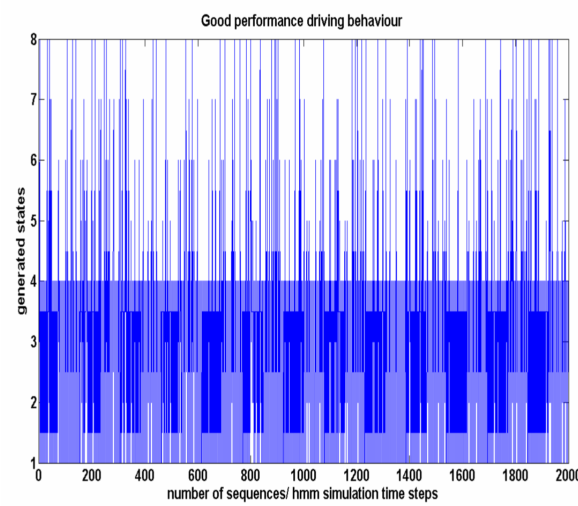

Figure 8. Good Performance with P=3.6, the driver performed the manoeuvres mostly in 1-4 range representing good performance

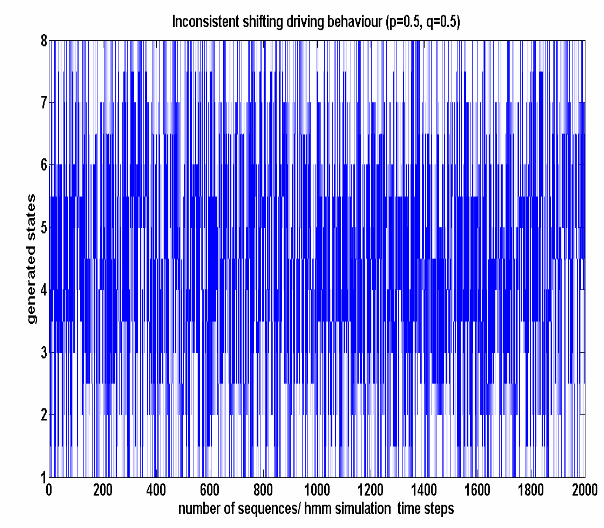

Figure 8. Inconsistent performance, P=2

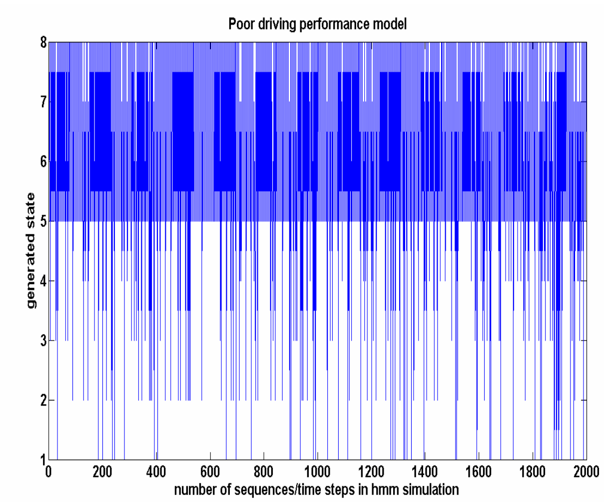

Figure 9. Bad performance, P=0.4, the driver is mostly performing in the bad performance area between [5-8]

IV. CONCLUSION AND FUTURE WORK

In conclusion, a different approach has been taken to model the driver manoeuvres in an urban road scenario. The approach has been demonstrated by examining the method step by step over one type of manoeuvre. HMMs are found to be promising in terms of modelling the manoeuvres once they have been broken down into phases corresponding to the physical meaning of the manoeuvre.

This study is part of the development of a larger system design for driver assistance and vigilance monitoring, which aims to fill the current gap in solutions for urban driving scenarios. In order to exploit fully the potential of the system described here, an extensive database containing more manoeuvres should be constructed. For this database real road experiments will be arranged, including more sensory channels. If driver movement and eye gaze signals can be included in the prediction of the algorithm, it is believed that the system will become less prone to false diagnosis and will be more accurate in its prediction of safety risk.

Future work includes constructing the new data base from on-road urban traffic environments containing at least twenty different drivers with different levels of driving experience. It is also promising to include dynamic time warping idea to better synchronise different signals from drivers and eliminate the non-linear time shift effects which are deteriorating the recognition performance.

The second important part of future work is to include vision-based systems and fuse this information with measured vehicle dynamics to get a better prediction of the planned manoeuvre.

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