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DRIVER'S BEHAVIOR MODELING USING THE HIDDEN MARKOV MODEL FORMALISM

Abstract. In this paper, we propose to model the evolution of data sensors during the driving situation encountered by a driver, using the hidden Markov Model formalism. We then use this modeling to identify in real time the current driver's aim. We tested the capacity of this modeling in a first experiment where we were able to categorize with an 80% success rate the driver's actions from their initial preparatory movements. Moreover, this formalism could give us information on the driver's behavior in certain situations. First we will describe the value of using this type of modeling in the field of transport. Then we will present the methodology we used to collect and analyse data on the driver's behavior. In the last section, we will present and discuss our results.

INTRODUCTION

One of the solutions being considered by the industry to increase traffic safety is the development of driving assistance systems. The objective of these technologies is to assist the driver in his task, by diffusing information and/or alarm messages, or even by taking control of the car.

The development of these technologies (systems of assistance, but also any other system functioning in parallel with the task of control) requires a better knowledge of the behavior of the driver, because assisting or informing the driver will always be done in a live situation. Not taking this situation, or the behavior of the driver in the situation, into account creates the risk of distracting the driver in his task at critical moments (whereas the driver was in fact in control of the situation). This would result in the simple rejection of such assistance systems.

Indeed, an adaptive assistance system must be able:

1. to understand the situation in which the driver finds himself,
2. to analyse his behavior,
3. to judge the adequacy of his behavior in the situation,
4. to adapt its assistance according to this judgement.

In the same way, the interaction of systems that are not directly related to the driving activity (telephone, PDA...) have to be managed (diffusion or not of message...) according to the driving context. (Bellet and Tattegrain-Veste. (2004).)

Our research is focused on the analysis of behavior (stage 2). We need to interpret the behavior of the driver in specific circumstances or a specific environment (is he overtaking someone, does he want to stop?) as quickly as possible and in real time.

This information, compared with the data on the environment, is an essential input to measure the adequacy of the driver in the situation, and so define the needs assistance. For example, if we understood that, when approaching a slow vehicle, the driver's behavior is still in "drive alone" mode, the suggested assistance could be an alarm indicating the vehicle in front. In another situation, for example, driving on a straight road, if we understood quickly enough that the driver's aim was to overtake the car in front of him, and we know that is a risky aim (because of an approaching bend or the approach of another car etc.), an alarm would be very useful for the driver. To increase comfort and safety, if we understood that the driver must not be distracted (for example, he wants to turn), we could also imagine stopping any phone or PDA activity,

All theses objectives cannot be achieved without having a real time analysis of the driving situation, based on the understanding and interpretation of the driver's actions. This is now technically possible on recent vehicles.

Indeed recent computerization of car architecture, based on the CAN (Controller Area Network) , gives us easier access to a large amount of data in real time, concerning vehicle dynamics and driver actions. Nevertheless these data, easy to collect, are often under-exploited. The main reasons for this are their sizeable number, plus the wide variety of driver behaviors and road situations. However these data contain some essential information about driver behavior. Thus, to process these data, techniques of statistical modeling could be of primary importance. Indeed, in order to process and compare the large amount of data collected, an automatic learning process which could make the model automatically match the experimental data is required. Furthermore, this learning process could result in information relevant for the research experts.

In order to achieve our objective, we need to create a base of behavior modeling. This base has to model the relationship between all driving situations and the evolution of the sensors in these situations.

However, if we want to take into account all driving diversity factors (traffic, infrastructure, aim of the driver in this infrastructure, weather, driving experience, age etc.), we require a large amount of data which, for the time being, is not possible to collect.

Also, we started to investigate the two most influential factors on driver behavior: road infrastructure (roundabout, straight line, intersection with red light etc.) and the aim of the driver in this infrastructure (to turn, pass, stop etc.). And we narrowed down the drivers' characteristics to two - middle age and experienced. So we studied the relationship between these two factors and driver actions and the vehicle dynamics. To model this relationship we used the Hidden Markov Models (HMMs).

One of the problems which emerged was how to process easily and in an exhaustive way all encountered driving situations. To solve this, we created a tool to analyse driving behavior based on an incremental learning process. We first tested this tool on experimental data recorded on one driver during one and a half hours. The result was good enough to continue our experimentation on more drivers.

In the first section, we will briefly describe how hidden Markov Models were applied in the field of transport. Then in the second section, we will present the methodology we used. And in the last section we focus on the results we obtained.

1. SCIENTIFIC CONTEXT

1.1 Some approaches to categorize the driving situation.

Given the complexity of driving analysis, the use of fuzzy methods, like Bayesian network, is relevant and effective in certain cases (i.e.: fuzzy forms (Peltier, 1993) and neurals networks (Pribes and Rogers, 1999)). They were only used to classify, in terms of danger level, a limited number of situations (intersection, dangerous motorway driving), but they do not calculate the consequence of the criteria on all road situations. Therefore the criteria were not robust enough for an analysis of all road situations.

We have already encountered this problem during earlier experiments: for example, the aim of the CEMVOCAS project was to develop a real time diagnosis of driver availability for receiving vocal messages without disturbing the driving activity. This system, working under real driving conditions, was able to provide an uninterrupted diagnosis, and to process any driving situation encountered.

The approach used in the project was that of neurons networks. This type of model has a learning process that can solve even high complexity problems. Nevertheless its main disadvantage is the obscure nature of the learned system: it is like a “black box”. The model that matches the data cannot be interpreted by an analyst. Therefore such a system cannot be improved by inserting an expert’s knowledge. CEMVOCAS allowed a successful classification of 85% of the situations in terms of availability (Tattegrain-Veste et al., 2001). However, improving the rates of recognition was difficult because of the complexity of the system interpretation. Indeed, the addition of new explanatory factors improved the recognition of some situations; but reduced it for others.

Another approach based on the rules of one group of experts brought the same rates of recognition. Moreover, its principal advantage was to allow an improvement of the rates for badly recognized situations, without changing the rates for others. Nevertheless, the development of the rules was quite long and difficult (manual analysis of data files and intuitive definition relevant criteria).

We then tried to define these rules by using traditional statistical methods (segmentation, classification) on the same experimental data (Dapzol, 2003). Nevertheless, the limits of these approaches lead us to seek models 1) with a learning process able to analyse a lot of data , and 2) with a possibility of interpretation that allow the validation of the model and the insertion of expert rules.

1.2 HMMS VIEW FOR THE CLASSIFICATION OF DRIVING SITUATIONS

In this section, after a short presentation on the Hidden Markov Models, we will present how these models are used to classify driving situations.

1.2.1 Hidden chains of Markov (HMMs): Brief summary of theory

These networks are based on the evolution of two processes. The first one E(t), evolving state by state, is invisible but determines another process O(t) visible. The second one is “what we can see of the world” (ex via the sensors) and the first one is “why the world is like that” (the driver wants to slow down, to turn etc). For example, in the field of voice recognition the invisible process are phonemes, and the visible process is the vocal signal. Two of these hypotheses are: there is an invisible process which evolves state by state; and the study of the visible signal could provide information on this process.

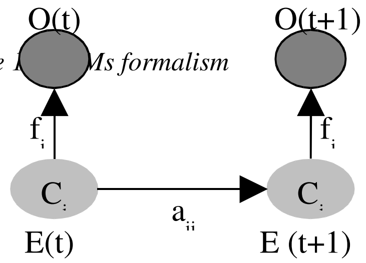


figure Ms formalism

Their first presentation in 1989 by Rabiner brought the development of effective algorithms both for the inference and for the learning. Their utilisation in various studies shows that HMMs are adapted to the problems with multidimensional nature where the time aspect is fundamental.

The relationship between the state of the invisible process and visible one is determined by a density's function (f_i) attached in each state i of the process E (see figure 1).
Many extensions of this model appeared (6). The last, closer to Software computing, are based on the use both of HMMs and of various data-processing techniques. (For example Oliver et al. (7) coupled HMMs with forms recognition algorithms).

1.2.2 Previous utilisation of HMMs in the transport field.

Studies in the area of cognitive modeling and research on driving activity showed that this activity could be divided into various phases with variable durations linked in a logical manner. In parallel, the study of voice recognition, a field of research with the same characteristics, directed us towards an effective formalism for modeling: Hidden Markov Model. Indeed, the formalism HMM is appropriate for taking into account the transitions between phases and for its structural possibility to model temporal dilations. We will present here only the studies on this formalism, in the field of transportation, which we considered to be the most relevant to us.

Forbes, and Al, (Forbes et al., 1995) from the university of Berkeley, working on automated driving (project "BATmobile"), developed a method based on input-output HMM of Bayesian Network whose state not only depends on the preceding state but also on the decision in progress. It showed that the architecture used brought a relevant solution to the problem of noise and uncertainties due to the sensor's sensitivity and interactions with the other vehicles, and that it was interesting to associate HMMs with expert rules. This driver model was tested by controlling a vehicle under a traffic simulator, and by checking that the behavior of the car was coherent.

A second application type of HMMs was carried out by Nechyba and Xu for the categorization of driving strategies under a simulator (Nechyba and Xu, 1998). A HMM is associated to each person. The alphabet used is based on behavioral criteria, obtained by vectorial quantification of the driver actions (defined by the spectra and the transform in wavelet of sensors data). To classify a new set of data (to know who is driving), an index of similarity between HMMs of the base and the one to be classified, is used. This index "able to compare stochastic, dynamic, and multidimensional trajectories" (Nechyba and Xu, 1998, p437) exceeds a traditional Bayesian classifier.

A third type of application takes into account the results in cognitive psychology describing the driving activity by successive states. For example, Liu and Kuge sought to characterize and detect road operations (Liu and Kuge, 1999). They showed how to model road positioning on the road (drive on a straight road, urgent lane change, ordinary lane change) by a series of HMMs. The result (the succes rate was 98.3% in categorizing the driver behavior), on dynamic simulator of control, shows the capacity of this approach to manage with the variability of behavior.

In the same way, Kumagaï, et al., were interested in the potentially dangerous situations on the arrival at crossroads, by predicting the following actions of the driver (Kumagaï et al., 2003). To do that, they used a detection model of the stopping sequence. An important concern of the paper of Kumagai et al., is "the topology interpretation of the model, in terms of the states, as well as the level of the states of the transitions" (Kumagaï et al., 2003, p119-120***). Although this interpretation is due to the simplicity of the variables used (the speed and braking), it convinced us even more of the advantage of using HMMs to understand driving activity.

Pentland and Liu modelled more diversified situations (stop at the next intersection, turn left at the next intersection, turn right at the next intersection, change lane, over-take car, go straight) under the simulator, (Liu et Pentland, 1999). They assumed that the human driving strategy on the vehicle is different according to the states of the driving activity. For example, they divided the lane change into six successive stages: (1) centre the car on the initial lane, (2) look if the opposite lane is free, (3) initiate the change of direction, (4) change of lane, (5) end of the change, and (6) centre the car in the new lane. With each stage, a Kalman Filter was associated, and each sequence was modelled by a HMM whose input parameters were the adequacy criteria with each filter.

They showed that this model had significant results. Indeed, 1.5 seconds after the beginning of the situation, the recognition was 95%. This research thus showed that we can quickly predict the driver's aim in a given infrastructure. It encouraged us to proceed in this way by keeping in mind the three following limitations:

- The data used by Pentland and Liu result from a driving simulator and are therefore purer than those obtained under real driving conditions. The real conditions bring an additional "noise" to the data due to the sensors and diversity of the driving situation.

- The authors used a restricted number of situations. Bringing new situations will decrease the recognition rate.
- Will the speed and rate of recognition be great enough to be useful in the assistance system? It could be unusable if 5% of confusion includes critical situations.

In our study, we tried to overcome these limitations by using a specific methodology which aimed to process real data and an unrestricted number of situations. This is the first step to designing an useful assistance system.

2. METHODOLOGY EMPLOYED

2.1 DATA COLLECTED

To identify the relationship between the encountered driving situation and the evolution of the sensors, we first validated our HMM approach by analysing the activity of one driver during one and half hours (90 minutes).

The experiment took place in town in the morning with little traffic and reasonable visibility. The subject was driving a "Citroen ZX" with four cameras (so we have 4 views: front , rear, the driver head , and his feet). Using the sensors of the car, we recorded in real time the driver's actions (action on the wheel, and on each pedal) and the state of the car (speed, lateral acceleration).

By using the process described below, the data collected were divided into 180 sequences, and these sequences separated into 40 clusters.

Since the first results are encouraging, future experimentation will consist of analysing the driving activity of 10 subjects on a larger circuit.

1. 2.2 THE LEARNING PROCESS

We wanted to build a base of driving situations . For each situation, we wanted to associate a set of examples (data collection) and a HMM modelisation. Nevertheless, we could not assume that our categorization of driving behavior in a real-life situation (defined by the infrastructure and the aim of the driver in this infrastructure) is right. The driver may demonstrate the same behavior in different situations; or he may demonstrate different behavior in the same situation. Therefore, our categorization had to match the data collection well, in order to combine the situations in which the driver has the same behavior.

Moreover we wanted to analyse the experiments in a exhaustive way (i.e: by analysing them from the beginning to the end), unlike the previous studies mentioned (which as a preliminary, selected the sequences to be studied from the results of their experiment).

So to build our base under those two constraints, we developed a procedure based on an iterative construction (see figure 2).

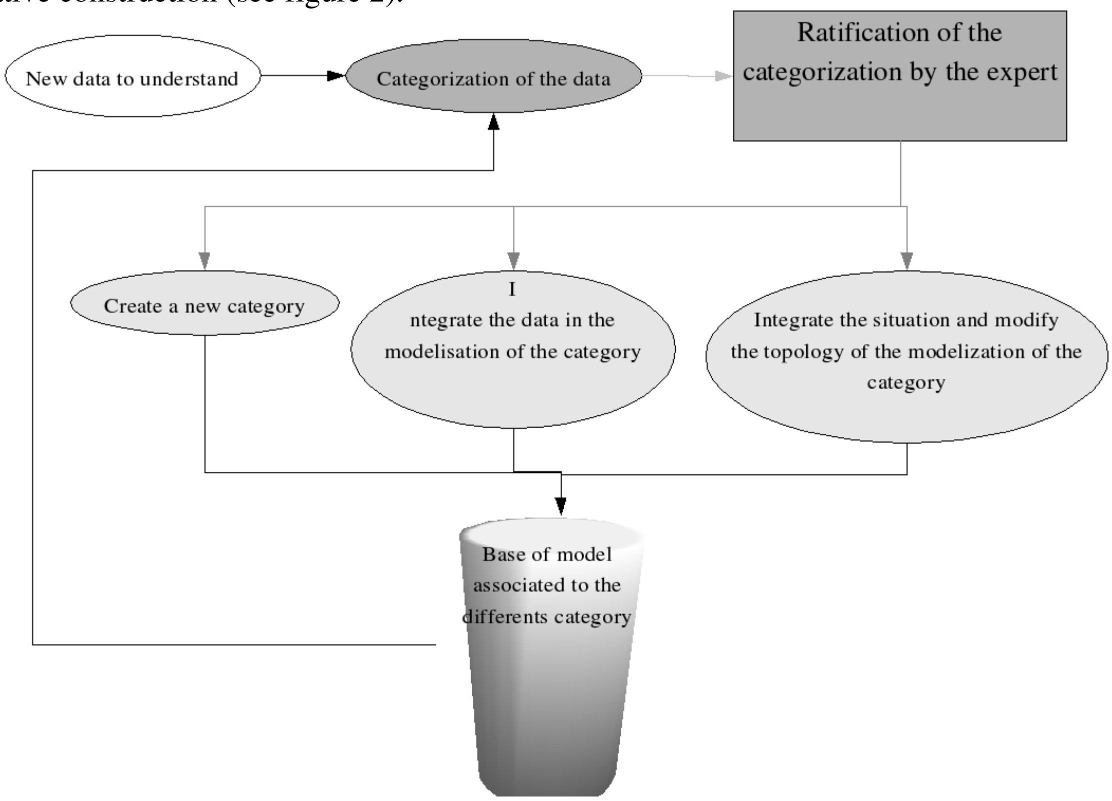


Fig.2: Sequence of the various stage of methodology. : All the experimental data is being processed , from the begining to the end, and the behavior base is updated each time a new example is not explained by an existing model. In this case, either a new model is added, or the model associated with the situation is enriched to integrate this example into it in order to take into account of the diversity of the behaviors.

This learning process is a semi-automatic one: practically, the operator starts by visualizing in parallel the video, and the evolution of the sensors. We calculate the evolution of the log-probability of membership of each situation. (Figure 3)

At the end of a certain amount of time (Tmax), if no situation is diagnosed by the sensor analysis or if the diagnosed situation is incorrect , the operator seeks, with the video, the end sequence which has not been recognised and codes the real situation (for example, “to start after red light + intersection + to go straight”). Then, the system inserts it in the base of behavior modeling.

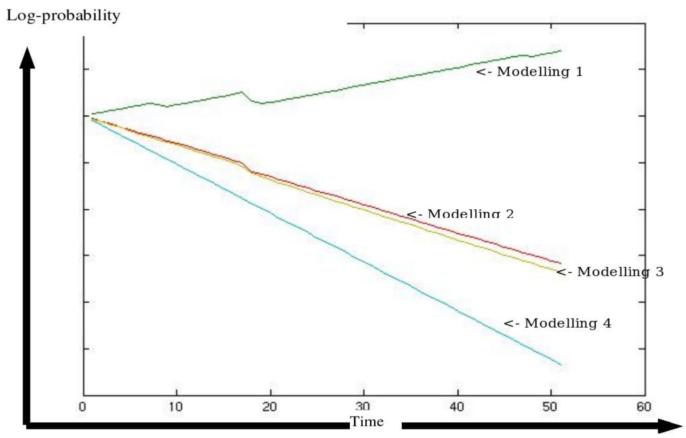


Figure 3: Evolution of the probabilities that the driving situation owns to the different models according to time

To do this, it builds a HMM corresponding to this one and optimizes the parameters of the model so that it corresponds as well as possible to the situation. To optimize the parameters, we used a mixed procedure that used both the statistical learning techniques and the knowledge of experts on the situation (labelling in the situation, what could be a general behavior, and what could be specific to the current sequence).

The software, created specifically, makes the utilisation and the interaction with the system easy (figure 4).

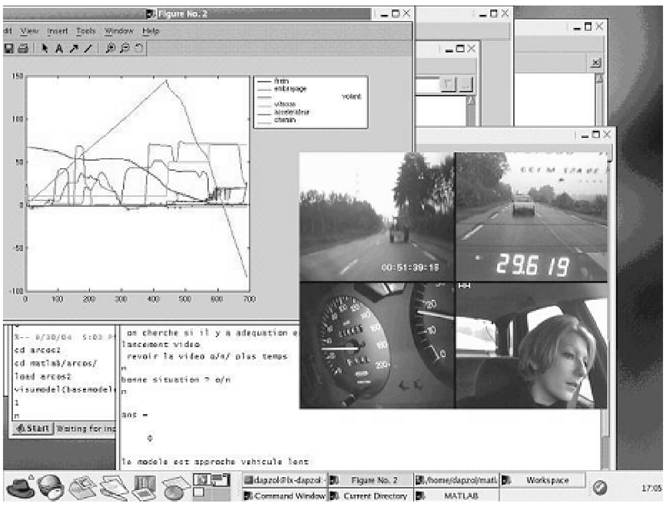


Figure 4: Interface graphic software

This methodology has several advantages. It allows us to study the whole of a course in a sequential way and thus, to classify the totality of the situations encountered.

It allows us to study all the experiment in a sequential way and thus, to classify every situation encountered.

The fact of being able to see the video sequence at the same time as the evolution of the parameters makes this interpretation easier.

Moreover, the fact that we can easily compare the predictability of the behavior modeling base and the real behavior of the driver, makes it possible for the researcher to know:

1. If the standard model needs to integrate this example to be more general,
2. If this situation requires a new model (for example to classify situations according to the traffic differently) or
3. If it is necessary to integrate into the model one of the parameters not used yet to differentiate it from another model (for example, new sensors....).

Lastly, this way of proceeding is intuitive enough to be used by a user not familiar with the Markovian processes. Thus, the methodology can be re-used to analyse the activity in other projects, either into confirmatory (i.e., to validate assumptions of differences between situations), or into exploratory (i.e., search for unknown situations bus not yet classified).

3. RESULTS

Our study produced results in two distinct categories: separating out driving activity (1) and predicting driver behavior (2).

3.1 SEPARATING OUT DRIVING ACTIVITY

It appears that the joint use of the Markovian models and the methodology could give information on driver behavior in road situations. This formalism is based on automatically dividing the sensors' evolution into several phases. These phases are homogeneous in terms of sensor variability. They could be interpretable (see figure 3). The interpretation could be done using both the parameters of the model and the division of the experiment's sequences.

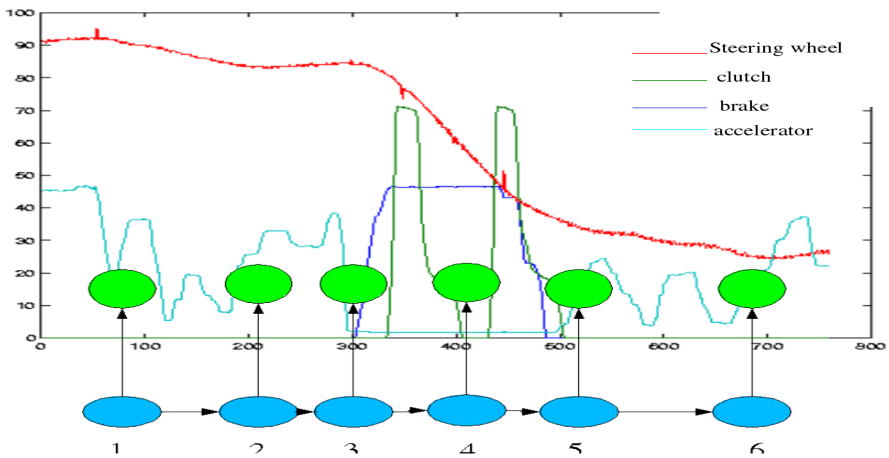


Fig.5: behavior of a driver arriving at a slow vehicle (tractor)

In this example, the driver sees a slow vehicle ahead. The various phases learned automatically by the software could be interpreted by the expert by mixing it with the video and the densities functions of the model. In this example, the expertise gained from ARCOS (Bellet et al, 2004) could bring us to label those phases as: 1) drive alone (to drive normally) 2) notice the obstacle (detecting the car ahead) 3) slow down 4) regulation (to strongly slow down) 5) stabilization (to stabilize his speed) 6) follow-up (to drive normally with a stabilized speed behind the vehicle).

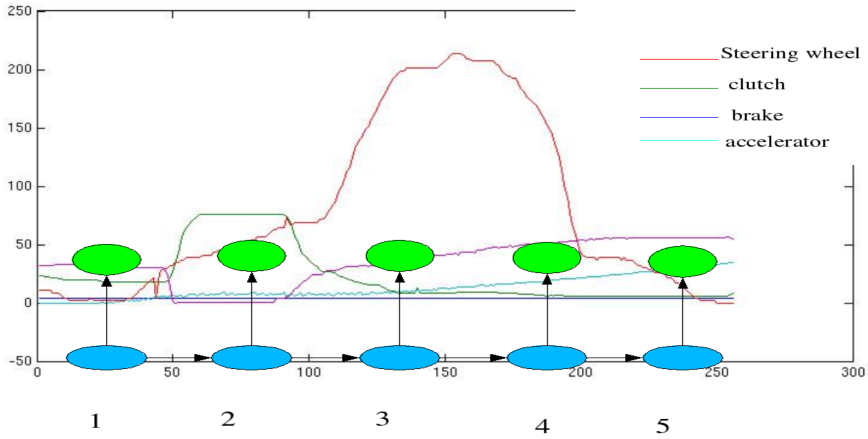


Fig.6: turn left after a red light at intersection

In this example, the driver turned left after a red light at an intersection (figure 4). Here the phases automatically learned could be interpreted as 1) stopped at the light 2) speeding up and beginning to turn 3) steering left 4) steering back to normal 5) stabilization : steering wheel near to the straight position and speed increasing.

This expert interpretation allows us to envisage more precise and adaptive assistance systems: this modeling allows us to know precisely which phase of the situation the driver is in. Thus, when approaching a slow vehicle, if the driver is still in the "normal driving" phase, the proposed assistance could be an alarm indicating the vehicle in front. Then if the driver is in the phase "slow down" but if the braking is not sufficient, the assistance could be either an alarm, or temporary control of the car. Then once the driver is in the stabilization phase, the assistance could help to stabilize his speed.

Of course, this separating out is not always meaningful. There are many sensors and the driving situation often seems too complex to label the various stages clearly.

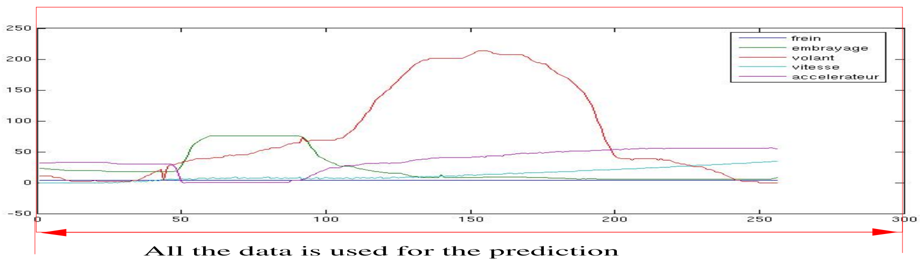
The separation into phases will be more efficient in future research because, at the time, all the parameters had an equal importance in the modeling of each situation. Nevertheless in some situations, it was important to know precisely which parameters were the most important in each phase of the situation. Future research will solve this problem by allowing a new type of information: the importance of each parameter in each phase.

3.2 PREDICTING OF DRIVER BEHAVIOR

To make adaptive systems of assistance functional, it is absolutely essential to be able to categorize the behavior of the driver in real time.

To be useful, this modeling must be robust and make an early categorization of the driver's behavior. To quantify its performance, our system was assessed according to two criteria:

- The first criteria, "off line robustness", was calculated on the totality of the situation (from the beginning to the end). For each sequence we calculated the probability that the situation belongs to each modeling associated with each situation. We kept the most probable situation for each sequence, and compared it to the real one. Thus it allowed us to measure the modeling capacity. Then we were able to identify and analyse the confusion between different HMMs modeling. In future, the possibility of using this "off line" modeling criteria could be used to label data automatically.



- The second criteria, "on line robustness", enables the modeling to provide a real time diagnosis of driver activity. We calculated it as for the “off line criteria” but, here, we used only the data from the beginning of each sequence to two seconds after. It is characterized by a rate of recognition and the time from which this rate is reached.

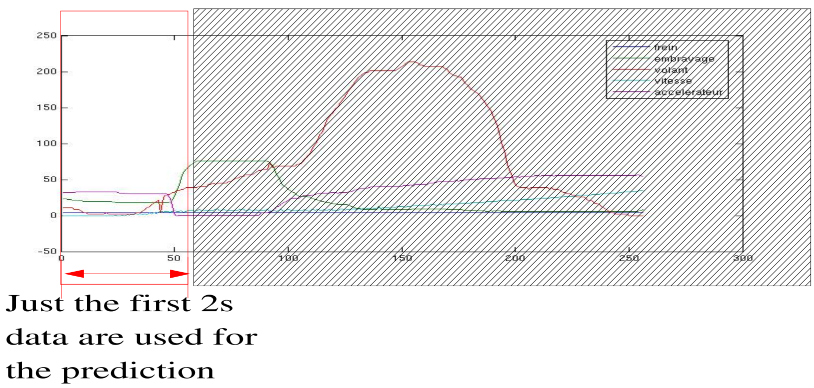


Fig.8: data used for “on line” prediction

For the moment, on all the encountered sequences, the "off line" success rate is more than 90%. The "on line" rate is 80 % two seconds from the beginning of the sequence. However, these results are limited because they only concern one driver as well as a restricted number of categories of driving situation (40). (roundabout+stop+turning left, straight line + passing, intersection + green light + going straight...).

To complete our base, we will conduct a new experiment: this one will involve 10 subjects. We will record their driving activity on an urban trip. This experiment will take place with the new experimental vehicle from LESCOT. This will enable us to have new types of data: inter-vehicle distance and road infrastructure.

CONCLUSION

In addition to the fundamental objectives, the methodology and the associated tool set allows the acquisition and analysis of driver behavior in a relatively easy way.

The interpretation of the models (dividing the driving situations into phases) is not the only important result for the analysis of driver behavior:

Also, the possibilities of this approach in predicting the current driver's situation, in real time, before the end of the driving situation, are very interesting with regard to the design of new adaptive assistance systems. In this case, the speed and the performances of the system interpreting the human behavior will be of primary importance.

Due to the complexity of the driver activity analysis, we need to combine different views: firstly the HMM formalism allowed us to model the sequential characteristic of the driving activity. However to use this formalism efficiently, we should combine it with statistical test and expert rules. Our approach, based on human expertise and statistical learning , allowed us to have an exhaustive analysis of the driving activity and then to build robust and interpretable models. The next experiment will increase the range of the models and their robustness.

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