A NEW MARKOVIAN MODEL TO CATEGORIZE DRIVING SITUATIONS

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ABSTRACT

In this study, we propose a new model to analyze the data sensors evolution during different situation encountered by the driver.
This modelling add to the classic Semi Hidden Markov Model (HMM) framework a weight feature.

We then used our modelling to identify the driver's aim and the driving situation he's in.
To assess the capacity of our modelling, we conduct an experiment which able us to record 718 driving sequences.
On these sequences, our modelling choice allows us to predict the driver's situation with a 85% success rate.
Moreover, this modeling gives some interesting results on the organisation of the driving activity.
These results show the HMM effectiveness to model and predict drivers behavior.

INTRODUCTION

To increase comfort and safety in vehicle, integrate communicative systems are developed. These systems could have various objectives and interact with drivers by different manners. Navigation systems, anticollision system, cell phone hand free car kit, are example of such systems.

Nevertheless, even if these systems often increase security, most of them don't take into account the driving situation when providing their assistance. Yet, trying to help the driver without knowing his specific behaviour and the specific situation he's in, bring the risk of giving him an inadequate assistance. This could disturb him at a critical moment [Bellet&Tattegrain, 2003]. To avoid this, the interectation with the driver has to be adapted to his own behavior.

Thus, the precense of a sub-sustem able to understand the current driving situation and able to manage the interaction with driver will increase system effectiveness.

The analysis of the current driving situation could now be done using the data on the vehicle dynamics and on the driver's actions collected at each moment on the vehicle via the CAN bus[1].

Nevertheless, in order to categorized the driver's current situation, every system need to compare a data temporal series with a library of driving situation modeling and then select the most adequate.

Unfortunately, modeling these data is complex. They are in large number,noisy , time-related and are changing according to the driver, the moment, and the environment characteristics.

Thus, to model the data recorded during driving situation, various modeling were used like linear system [weir & Chao 2005], statisticals techniques or neural network [Peltier 1993].

More recently the Hidden Markov Model (HMM), previously used in the voice recognition field, was also adapt to model the driving data evolution. These researchs ([Forbes & al, 1995] [Pentland & Liu, 1999]) show that this modeling seems adequate to understand, model and predict driver's behaviour.

Indeed, a modelling applied on the driver behavior data has to process multi-dimentionnal and temporal data. Moreover, it appears that to be effective a modelling has to intergrate 3 characteristics.

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1 Controler Area Network : data bus, develop by Bosh in the 80's, for the serial communication in the vehicle, was ISO-normalised. Now it's commonly used in car to easily access to vehicle data.

1. *Existence of efficient algorithms to estimate the modelling parameters:* Although, some authors point out that methods based on expert rules give interesting results in both terms of prediction, and behavior analysis, these methods are built upon the visual analysis of the data and the definition of relevant criteria. They required a long process of analysis and error/success [Bellet & al 2004]. So, due to the large amount of data and their complexity, an automatic learning process is necessary.

2. *a real-time adequation criteria of new data set to a model* : In order to help the driver in a secure way, the situation he's in has to be quickly categorized.

3. *the modeling interpretation :* Due to the large diversity of driving situations, the record of a few set of example during an experimentation can be biased by uncontrollable factors (weathers, traffic ...).
The presence of these factors could bring “noise” and change normally recorded data in these situations. Thus, when a modelling is build on this data, we need an expert point of view to valid /infirm his capacity to be a general modelling.
Indeed, in [Pribe 1999] authors show that neural network give good results. Nevertheless, the recognition rate was low for some specific situations. As this modelling is like a “ black blox”, understanding mistakes was difficult and so was the improvement of the modelling. Thus, in order to have this expert point of view, the modelling has to be interpretable in term of driving activity.

The HMM has these 3 characteristics which makes it usefull to model the data on driver behavior.

1. Baum-Welch adapted the Expectation-Maximization learning algorithm to this framework [Baum & Eagon, 1967]. This algorithm can determine the models parameters that locally maximize the log-likelihood of the data.
2. The Forward algorithms could determine in real time the adequation between a data set and a modelling [Oliver & Pentland, 2000].
3. Kumagai et al used the simplicity of the Hidden Markov Modelling to interpret the structure in term of driving activity. They show that the HMM give information on the succession of driver's actions and state regarding a particular situation [Kumagai et al, 2003].

Using these characteristics, previous studies using this modeling obtained satystifaying results.

However, they used complex sensors and analyzed a small panel of driving situations.Nevertheless, to be usefull a categorization system has to be able to use basic sensors and to analyse a large panel of driving situations.

To fullfill these objectives, in this paper, we will first define a driving situation as a period of driving time where the driver has the same tactical objective (turn, overtake,...). It's characterized by the aim of the driver , the infrastructure (round-abound, straight road, intersection,,..) and the initial characteristics of the situation (initial speed, position on road).

Thus, we aim to build a base of driving situation modeling using HMM. This will allow us to define for an unknown sequence of data in which situation it may belong.

To achieve these objective, we choose to make the HMM more adapted to the driving data analysis by integrating characteristic issued from knowledge on driving behavior.

Thus we develop a specific modeling, the Weight Semi Hidden Markov Model (WSHMM) based on the HMM framework.

Moreover as we study a large panel of driving situations, some situations seems very closes in terms of driver behavior regarding the sensors used.

To manage with this problem, we have to develop a new technic to manage with the promixity between different situations.

To expose this research, this paper is organized as follows. In the first part, after a short presentation of the HMM formalism, we will present here the studies on this framework, in the field of transportation, which we considered to be the most relevant. The second section defines the WSHMM and the algorithm developped. In the third part, we will expose the experimentation made. Finally, we will present and discuss our results.

1 HIDDEN MARKOV MODEL

presentation

The Hidden Markov Model (HMM) is a stochastic signal modelling. It aims to model discrete or continuous multidimensionnal signal by a random process.

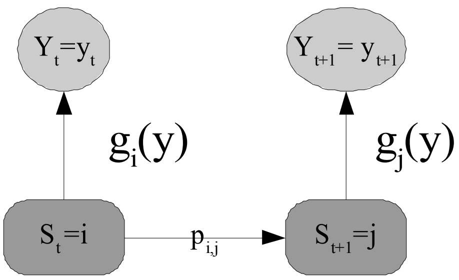
This framework supposed that the signal evolution can be considered as the evolution of 2 processes (illustration 1). The first one is the visible signal, like what we can recorded from the sensors. It's said to be the visible process, named **Y**. Its value depends on another process. This second process **S** is why we can see that on the first process at each moment. Its values are not directly observable but can be derived from the analysis of **Y**. This process is generally evolving state by state i ($i \in [1 : N]$ and $N \in [1 : \mathbb{N}]$) and fit the classic Markov constraints [Rabinner, 1989].

For each state "i", the relation between Y and S is a probabilistic one defined by a density function g_i (figure 1).

This modelling is classically defined by 3 parameters.

- p_{ij} =P(S(t)=i / S(t-1)=j) $i, j \in [1 : N]$ (the probability that S is in state "i" at time "t" knowing that E is in "j" at time "t-1".
- π_i $i \in [1 : N]$:the probability that S is in state "i" at time "t" knowing that E is in "j" at time "t-1".
- θ_i $i \in [1 : N]$: the density function attached to each state "i"

figure 1: classical representaiton of Hidden Markov Model



The model structure allow to it process **temporal and multi-dimensionnal** data in a large amount**.**

These qualities were first successfully used in the field of voice recognition. In this field, the invisible process was phoneme and the visible one the vocal signal.Using the vocal signal, word said could be precisely diagnosted.

It's now used in various applications like gene research , eye tracking or driver behavior recognition.

Hidden Markov Model and driver behavior

Indeed, for the driver behavior recognition, this model appears to be adapted.

From a theoretical point of view, some authors show that the driver behavior in a situation could be divided into several phases linked in a logical manner. For example Salcucci propose to describe the overtaking by different typical phases: "weak acceleration", "lane changing", "strong acceleration", "straight and fast driving", "return on previous lane", "deceleration"[Salvucci & Liu, 1999] .

These phases could be modelled as the state of the invisible process. The value of the visible process would be what we can record on these phases: activity of the driver (pedals and steering values) and vehicle dynamics (speed, acceleration).

Kumagai et al shows that HMM could be used to interpret driving activity as a succession of phases. Indeed, they were interested in the potentially dangerous situations on the arrival at crossroads, by predicting the following actions of the driver [Kumagai, 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". 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 HMM to understand driving activity.

This link between HMM framework and driving activity partially explains the good results of this modeling to categorize in real time the driver's behavior ([Kumagai, 2003],[Oliver & Pentland, 2000], [Pentland, 1999]).

The research made by Pentland and Liu is significant of this fact. Indeed, using HMM, Pentland and Liu modeled 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) center 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) center the car in the new lane. With each stage, a Kalman Filter was associated, and each sequence was modeled 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 when using HMM, we could quickly predict the driver's aim in a given infrastructure.

The previous work on the driver behavior modelisation using HMM encouraged us to proceed in this way by keeping in mind the three following limitations:

- All the sensors used in these study aren't available in most of the vehicles (eyetracking, lateral positioning sensors) . So using the modeling in real application is not an easy. Moreover, it's difficult to know if the results came from the use of high-performance sensors or from a good modeling.

- Most of the authors select only few situations to compare. As it exists a great number of driving situation, their results are biased by this short view of the driving activity. So, in order to understand the difference between driving situations and to build efficient diagnostic module, it's important to model the maximum number of driving situations.

- 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 order to resolve these three limits, we suppose that using driving expert knowledge to develop a specific HMM will increase modeling efficiency.

Indeed, preliminary researches shows that driving activity has two important particularities.

1. From a psychological point of view, the driving activity could be divided into phases [Bellet,1998]. Moreover experiences show that these phases are relatively stable. We choose to model this kind of constraint. In order to integrate this important characteristic, we will use Semi Hidden Markov Model [Rabinner, 1989].

   This modeling is an extension of the HMM framework which allow *to precisely model the time spent in each state*. Moreover, we suppose that *time spend in each state must be superior to 1 seconde.*

2. According to situations, some sensors may bring more information than others [Salvucci & Liu, 2002]. For example, to model a “Turn left”, the steering wheel seems more important than the speed of the vehicle. So, we were conducted to use a weight concept on the variable. To implement this specificity we develop a specific modeling the weight Hidden Markov Model.

   This modeling allows us to define for each situation and for each state, *what variables are the most relevant.*

To solve the limits of previous experiment, we choose to integrate theses 2 particularities in a HMM. So, we develop a specific modeling the Weight Semi Hidden Markov Model (WSHMM). This modeling integrate the capacity of specifically model the time spent in each state and the weight feature which is important to define the important variables for each state.

2 WEIGHT SEMI HIDDEN MARKOV MODEL

To improve the efficiency of the Markov model, some authors propose various extensions. These extensions are usually constraints fixed on the model and chosen using some specific knowledge on the studied phenomena [Pal & Hu, 2001].

Voice recognition studies brings a lot of new and specific modellings. For example, Factorial Hidden Markov Model and Hierarchic Hidden Markov Model are designed to model the different language level [Fine & al, 2001] and Coupled Hidden Markov Model is designed to integrate different information sources [Oliver, 2000].

An easy way to insert specific knowledge on the HMM is to model explicitly the time spent in each state. The Semi-HMM were designed to that purpose [Rabinner, 1989].

In all cases, all the dimensions of the studied process have the same influence on the hidden process.

Nevertheless, this hypothesis is often unwarranted. To our knowledge, except Heiga et al [Heiga & al, 2004], no study introduce the concept of weight on the dimension of Y.

These authors were focused on the events union $(Y_t^r = y_t^r)$ each weighted by a factor " $c_{j,r}$ ", with r the r[nth] dimension of y. The density function associated with each state i is then defined as :

$$g(y_t \mid S_t = j) = g_j(y) = \sum_{r=1}^{R} c_{j,r} g_{r,j}(y^{(r)}),$$

with $\sum_{r=1}^{R} c_{j,r} = 1$ and R=dim(y). They established reestimation formula for this specific density function.

Definition

In this paper, we propose to apply the concept of weight on the events intersection $(Y_t^r = y_t^r)$.

So, we introduce $c_{j,r}$ for j=[1:K] and r=[1:R] ,with R the dimension of y, and

$$\tilde{g}_j(y) = \prod_{r=1}^{R} [g_{j,r}(y^{(r)})]^{c_{j,r}} \quad with \prod_{r=1}^{R} c_{j,r} = 1 \; . (1)$$

$y^{(r)}$ is the r^{neth} dimension *of y*.

$c_{j,r}$ is the weight associate to the r^{neth} dimension for the j[nth] .

and $g_{j,r}$ a Gaussian density with parameters $[m_{j,r}\ ,\ \sigma_{j,r}]$.

So an HMM with such a density function has these parameters $\theta = \{\pi, p, m, \sigma, c\}$.

Algorithmes

To be useful, an Hidden Markov Model has to have at least 3 problems solved [Rabinner1989].

a) estimation of the probability of an observation

b) estimation of the hidden state $s_{1...T}$ who most probably generated $y_{1...T}$

c) model parameters estimation.

For the 2 first problems, classic solutions could be found in [Rabinner, 1989] by replacing g_i by (1).

For the problem of determining the model parameters, we used the E-M algorithm [Dempster & al, 1977]. This algorithms was adapt by Baum and Welch to the particular case of HMM, and consist of an reestimation process of the model parameters. This process converges to a local optimum of data likelihood [Rabinner, 1989].

Thus, using theses results, we algorithmically solve the 3 classics problems and make this modeling usable to analyse driving activity [Dapzol, 2006].

3 EXPERIMENTATION

To assess our model, we conduct an experimentation which aims to record behaviour data on various real driving situations. We choose to study the specific effect of infrastructure and driver's aim on behaviour. So, we fixe other factors which could influence the activity.

The 5 subjects were chosen in order to have a homogeneous population in term of age and experience of driving (about 40 years old and experiment drivers).

The instruction was to drive naturally (overtake if they feel it necessary; go to the speed they want…). Furthermore, in order to interfere less than possible, the driving direction were given as soon as possible.

In the same way, the duration of the experiment was about only 1h (depending on trafic) in order to the driver tiredness didn't change his behaviour. At last, the experiment took place only when the weather was sunny and the visibilty satisfaying.

Subjects had to drive in predetermined urban course. This course was situated in town and motorway and was chosen to include various driving situations (intersection and turn left, round abound and go straight….).

We use the experimental vehicle MARGO which allows us to record data :

- from the driver (clutch, accelerator, steering wheel, …),
- from the vehicle (speed and longitudinal acceleration),
- from the environment (the front and the back scene were recorded on a video).

Software developed in LESCOT allows us to synchronize, visualize, and analyze these data. With this we defined driving sequences by a period where the driver has a homogeneous tactical aim and we characterized theses sequences by

- the urban context (town, motorway…)
- the initial speed,
- the infrastructure,
- the aim of the driver (as categorised from an expert view),
- the different events which occurred in the sequence – pedestrian crossing the street, car overtaking the driver –

In this way, 1209 driving sequences were defined, interpreted and characterized by those previous factors. The average sequences length is about 15 seconds. Of course each of them was associated with sensors evolution data.

Then, we defined "driving situation" as a group of sequences homogeneous in term of urban context, infrastructure, aim of the driver, and the initial speed.

Unfortunately, some external events change the normal organization of the driver's action (activity of another vehicle, change of light when crossing an intersection...). So firstly, to model the driver's action, we just keep sequences without external events (718 sequences) .

To allow the constitution of a group of test sequences and of learning sequences for each situation, we keep only situations with more than 5 sequences.

We then have 36 situations respecting in accordance with this criteria (turn-left at medium speed in an X intersection , overtake at low speed in a straight line ...)

In each situation, we have 19,5 sequences on average (see [Dapzol, 2006] for more details).

We will now use these data to implement and test our modelling.

4 RESULTS

In this section, we will present results obtained using our new model, and a method we developed to manage the diversity of driving situations.

Model Implementation Method and Partitions Definition

We associated each of the 36 driving situations with a WSHMM which has θ_d as parameters.

Each of these driving situations $d \in [1:36]$ was also associated with a set of recorded data sequences $\{SD_{d,q}, q \in [1:N_d]\}$, with N_d the number of sequences for the situation d. These sequences were divided in two groups: the learning one with N_d^L sequences (126 sequences in total) and the test one with N_d^T sequences (592 sequences in total).

Using the reestimation formulas presented in (2), we computed for each WSHMM the optimal parameter of each modeling (the matrix of transition, the matrix of weight and the different parameters of the normal distribution of each state).

To optimize the number of state and the topology (the diffenent link between states), we use topology learning algorithms and expert validation which are presented in [Dapzol, 2006].

Although we optimized each model parameters, driving situations are sometimes very similar. For example, depending on the driver and on collected data, the behavior while turning in a T intersection and turning in an X intersection often seems the same.

So, in order to avoid confusion, we choose to group some situations and to define different partitions of all the situations. As models can be very different in term of topology and learning sequence number, we developed a specific method.

This technique is based on a probabilistic distance between situation and hierarchic ascending classification ([Dapzol, 2006]).

So, we considered firstly every situation separately. Then we computed the distance between each of them.

To computed the distance between 2 situations, we chose the pseudo-distance defined by Nechyba & Xu for the HMM [Nechyba & Xu, 1998].

$$\delta(M_1, M_2) = 1 - \sqrt{\frac{P(SA_1|M_2)P(SA_2|M_1)}{P(SA_1|M_1)P(SA_2|M_2)}}$$

With SA_i the learning sequence associated with M_i and if M_i correspond to more than one situation

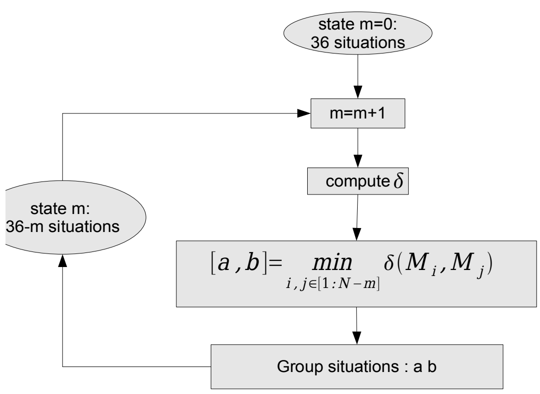
$$P(SA|M) = \min_{k \in [1:m]} P(SA|M_k)$$

.

This distance has the advantage to evaluate the proximity between models with different dimensions by computing the model likelihood regarding the learning sequence associated to each one.

The process consist in considering firstly all the modelling then computing $\delta(M_i, M_j)$ $\forall i, j = [1:36]$ .When this distance is computed, the 2 closest situations are grouped. Then we process iteratively. δ is re-calculated on the new partition; and another, the 2 closest partition are grouped. This process is done until one group stayed (figure 2).

figure 2: hierarchic classification process to group driving situations.



At each step, we computed 2 rates:

- The global rate equals to the number of sequences well recognized divided by number of sequences for all situation.
- The normed rate equals to the mean of recognition rate for each situation

The evolution analysis of these 2 rates shows that between the 10th and the 17th grouping the 2 rates are closed. So at this time, errors are uniformly dispatched between situations. Before the 10th grouping, some situations are badly recognized (like changing lane). They make the normed rate decrease. After the 17th grouping, these situations are grouped and then recognized. The normed rate goes higher than the global rate.

Moreover, at the 10th and 18th grouping, a break appears in the rate evolution. Thus, we define 2 partitions of the total number of situations.

- a large partition which is composed of 26 groups of situations (the recognition rate here is 75.35%)

In this partition, the situations grouped are those close regarding the infrastructure. For example, situation in a « T intersection » and in a « X intersection »with the same objective are grouped. The type of sensors used and the proximity between behavior in these two infrastructures bring confusions between situations. To avoid this, another sensors are required like eye tracker or gps.

- a medium partition which is composed of 18 groups of situations, (the recognition rate here is 87.88%)

In this partition, situations with a large panel of possible behaviors are grouped together. For example, the situation « changing lane » correspond to many different behaviors. It's confused with « follow lane in light curve ». Here too, another sensors could help us to decrease the number of confusions. Moreover, to build a robuster modeling, situations with heteregenous behavior could be divided into different one in order to have « one situation one type of behavior ».

Another partition seems important. The first one where the recognition rate goes further than 90%. This partition is formed after the 24th grouping and is composed of 12 groups of situations (the recognition rate here is 90,53%).

Test

We tested our modelling effectiveness on these 3 partitions using 2 criteria "off line diagnostic" and "on line diagnostic".

For each $SC_{d,q}$ of the 592 sequences ($d \in [1:36], q \in [1:N_d^T]$) in our test base and for each modelling $d \in [1:36]$, we calculate the probability that the sequence is own by the situation "d" $P(SC_{d^*,q}|\theta_d)$.

A sequence own by the situation d* is recognized when the most probable situation is d^* .

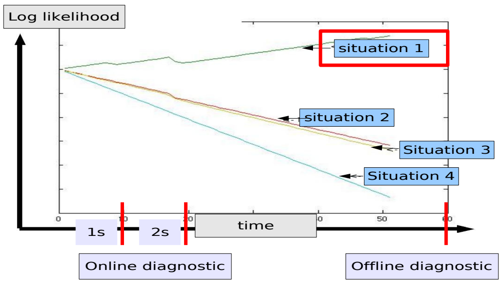


Illustration 3: likelihood evolution according to a data set and a collection of modeling

$$P(SC_{d^*,q}|\theta_d) = \max_{d \in [1:36]} P(SC_{d,q}|\theta_d) .$$

Moreover, using the Forward-Backward algorithm, for every time t_0, we calculate the probability that the sequence is recognized before t_0.

At last, for a group of situation, we said that a sequence own by the situation d_0 is recognised when the most probable situation is in the group of the situation d_0.

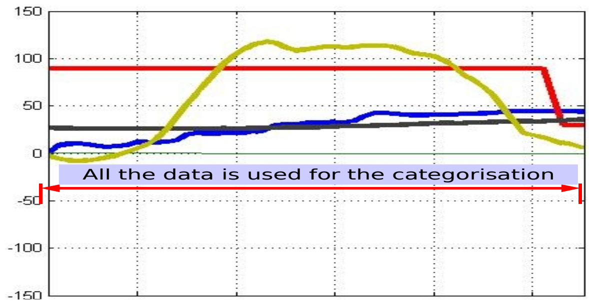
This comparison was made on all the test-sequences.

Moreover, to point out the real utility of our modeling specifity, we test different kind of modeling (HMM, Semi-HMM, and Weight Semi HMM).

"off line diagnostic"

The first criteria is evaluated on all the data of each test sequence (figure 4). This criterion is useful to test if the modelling was able to discriminate different patern for each situation.

figure 4 : In order to determine the recognition rate « off line », all the data of each sequence are used to make the categorization



In future, the possibility of using this "off line" modelling criteria could be used to label data automatically.

The next chart shows the recognition rate for the different partitions and for different modelling types.

The integration of the two features in the proposed modelling appears important to make a diagnostic on the small and the intermediate partition. For the large partition, some of the driving situations are very close. So the learning process converged to a weight matrix very close too. The weight concept can't be useful in this case.

On the contrary, the WSHMM seems more effective than the HMM for the small partition (91% vs 88%) and a lot more for the intermediate partition (88% vs 80%).

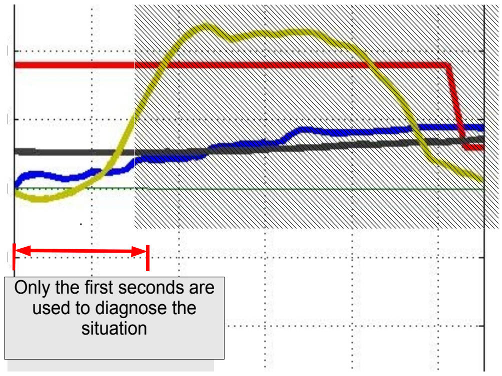
These results confirm our choices in our modelling. Indeed, if a small number of situations could be classify using HMM, a large number of situations brings a supplementary complexity. The integration of specific features matched with the driving activity characteristics (weight, time modelling) could be a solution to this problem.

Finally with less complex sensors, and a number of situations increased, we are closed from the previous studies ([Pentland, 2002], [Kumagai, 2003]).

On line diagnostic

We also tested our modelling with a second criterion. The "online diagnostic" was calculated using only the t_0 first seconds (t_0=1,2) of each sequences (illustration 5). This criterion is useful to evaluate the model capacity to give an earlier diagnostic.

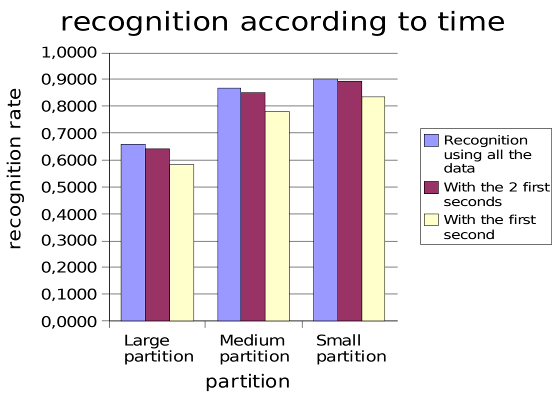
Illustration 5: on ligne diagnostic



In this case, the recognition rate was good (75 % for the intermediate partition and for a recognition in 1second). The rate "online" 2 seconds after the beginning after the sequences is close to the rate "offline" (see illustration 6).

Moreover, confusion seems not due to a modelling problem but due to an intrinsinc difficulty to discriminate some situations in the first seconds. Indeed for some situations, the simplicity of the used sensors doesn't allow us to predict the situation earlier. For others, only the analysis of the final state of the vehicle could categorize them correctly.

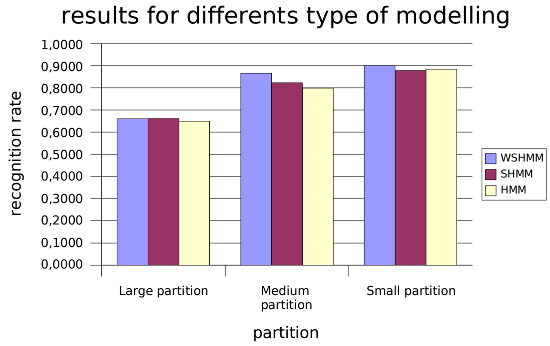
Illustration 6: recognition rate according to time using WSHMM



For example, sequences where the driver turn in an intersection and sequences where the driver stop are badly recognised with only the data of the first seconds. Only the study of the eye movement could improve the recognition rate.

Finally with less complex sensors, and a number of situations increased, we are closed from the previous studies ([Pentland, 2002], [Kumagai, 2003])

Illustration 7: recognition rate for the aposteriori criterion according to modelling type



Results for unusual behavior.

We also test the capacity of the WSHMM to categorize unusual behavior.

Indeed, in some sequences, the driving situation was unusual. The difference could be due to external events (unpredictable obstacle, unexcepcted behavior of another car) or due to unusual behavior (the driver didn't see the light, the infrastructure,...). Results for these sequences are given in the chart above.

Illustration 8 recognition rate comparison between n prototical sequences and unsual sequences. The comparision is made a posteriori, with all the data of each sequence, or with only the first one or two second of data of each sequence.

		Protypical	Unusual
A posteriori	**Large**	0,6605	0,476
	Medium	0,8666	0,671
	Small	0,9020	0,793
2s	**Large**	0,640	0,463
	Medium	0,850	0,659
	Small	0,892	0,774
1s	**Large**	0,640	0,463
	Medium	0,850	0,659
	Small	0,892	0,774

Although the recognition rate for unusual sequences is less than the one on prototypical one (49% of sequences well recognised for the large partition versus 66 % for the prototypical), it's still satisfaying for the small partition (the rate is almost 80%).

The recognition rate difference between usual sequence and unusual one is approxitavely constant and is equals to 15-20%.

This implies that for a part of unusual sequences the change of the driving activty is too important to be model with the same modeling as the one for protoypical one.

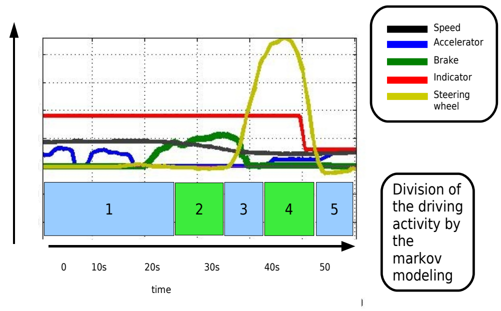
Separating out the driving activity

The markovain modelings could give earlier diagnositc of the driving activity. Morevorer, it appears that this modeling could give information on driver behavior in road situations. In fact, this formalism is focused 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.

The figure 9 shows a situation where the driver turned left after at an intersection (figure 4). Here the phases automatically learned could be interpreted as 1) drive normally 2) see the intersection / starting to decelerate 3) steering left 4) steering back to normal 5) stabilization : steering wheel near to the straight position and speed increasing.

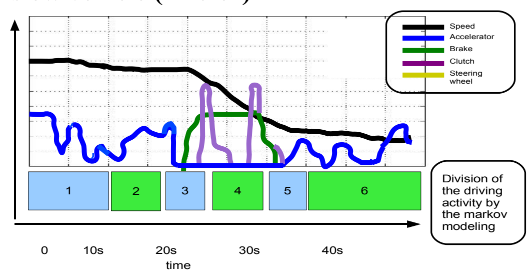
This expert interpretation allows us to envisage more precise and adaptive assistance systems: this modeling allows us to know precisely which phase of the situation the driver is in. Thus, when approaching a slow vehicle, if the driver is still in the "normal driving" phase, the proposed assistance 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.

Illustration 9: driver's behavior when turning left at intersection / middle speed



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).

Illustration 10: behavior of a driver arriving at a slow vehicle (tractor)



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.

Conclusion

To manage in a secure way the interaction between driver and electronics devices, driver's behavior has to be analysed and categorized. This will assure the driver to have the most adapted assistance/information according to his situation.

In order to categorized the driver current behavior, a modelling of the driver's actions according to a specific situation had to be developped. This will allows us to underdstand in real time in which situation the driver is in.

In this study, we propose a new modeling based on the HMM framework. To achieve our objectives, we extend the HMM to the WSHMM by using the SHMM and adding a weight feature. Then for this modelling, we develop efficient algorithms for both the inference, the decoding and the learning process.

To test our model, we conduct an experiment in real conditions which allow us to record various data on the driver behaviour.

Finally, we assess our model using two criteria which shows that comparing with other modelling type, our modelling choices increase the recognition rate.

We show that with more situations analysed our results are closed than those of previous studies.

Furthermore, the modelling proposed seems to be adapt to point out the sequential characteristic of the driving activity.

From a practical view, the weight feature and algorithms associated could be used to find which variables are necessary to discriminate situations. This could be used to choose the right sensors regarding an application.

Nevertheless to make the system useful in vehicle, recording data and studying more complex situations and different types of driver will be necessary.

This will have to be done integration of pre-processing techniques for the variables. At last, even if the mains study consider driving as a series of independent driving sequences, a long term dependency between sequences exists. Integrating this characteristic will improve not only the recognition rate but also knowledge on driver behaviour.

At last, nowadays new studies bring large flow of data. Now these data are manually analysed and divided into several driving situations. Test are now in course to use our modelling mixed with break-point modelling to automatically process all these data. This will shorter the time spent on the analysis and decrease the possible mistakes.

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