CONTEXT-AWARE DRIVING BEHAVIOUR MODEL

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ABSTRACT

Existing driving behaviour models have a strong emphasis on the driver's cognitive components including aspects such as motivation, risk assessment, attention, compensation, capability, workload, individual traits and experience. Each existing model was designed specifically for a particular driving situation such as speeding or fatigue. A general and comprehensive model is still unavailable despite 60 years of research on the topic. No consensus has been reached mainly due to the inability to generalize, operationalise and validate these subjective cognitive models in real driving conditions. This paper defines a framework for a new context aware driving behaviour model capable of predicting driver's behaviour. This approach broadens the cognitive focus of existing driving behaviour models to integrate contextual information related to the vehicle, environment, driver and the interactions between them. The theoretical model is an information processing, probalistic based model. Context awareness concepts from the Ubiquitous Computing research community are integrated into the model. Such integration improves the descriptive power and generalisability of our driving behaviour model.

I INTRODUCTION

Driving behaviour models explain and predict the behaviour of drivers. Existing models are largely subjective and based on self-report scales (Ranney 1994). They strongly emphasise the driver's cognitive state and have incorporated important behavioural change concepts such as motivation, or risk assessment. However motivational models such as risk compensation (Wilde, 1982), risk threshold (Naatanen *et al.*, 1976) or risk avoidance (Fuller, 1984) remain highly subjective concepts. For example, risk is often associated with perceived probability of harm or negative event and its severity. The measurement of perceived risk is often focused at the probability of the risk. The probability of negative event is rarely the same for everyone and varies per circumstances. The possible use of a baseline measures to compare risk perceptions is debatable. Understanding one's personal sensitivity to risk requires knowledge of other factors—such as personal behaviours, family history, and environmental exposures—that determine that probability (Weinstein, 1999).

Although the driver is the main actor in the driving activity, driving is not an isolated activity. It takes place in a wider context in which the driver constantly interacts with its immediate environment and the vehicle. The observation of how drivers actually act on the road, also known as "driver behaviour" as opposed to "driver performance" (what the driver can do, e.g., perceptual and motor skills), has generated significant body of work in which traffic psychologists have played major roles (Dorn, 2003). Driver behaviour and driver performance have mainly been used to analyse factors contributing to crashes. Pre crash analysis to create predictive models as well as post crashes analysis to identify contributing factors leading to crashes are the two complementary approaches used to address crash prevention. The contributing factors as broad as cognitive abilities, social context, emotion, driver's trait, experience, hazard perception skills and so on have been identified as driver's individual factors affecting driver's performance.

The situation in which the driver evolves plays a crucial role in determining the type of actions. A situation is also called context in the rest of this document. Existing "cognitive" models do not take into account the dynamic nature or context in which a driver's actions evolve. Without the context, the validation of these models in real driving situations would be difficult. The lack of a data based model to predict drivers' behaviour is a major weakness of existing models. A generalizable and comprehensive driver behaviour model has yet to be developed, despite 60 years of research on the topic. Therefore context is essential to explain driving behaviour and to improve the generalizability and reliability of existing driving behaviour models.

Section II describes related work. Section III describes how we approximate cognitive models to computational models. Section IV briefly describes contest aware systems concepts that we use to predict driver's behaviour. Section V presents our context aware prediction framework based on Bayesian network. Section VI describes what a Bayesian network is and how we use it in our framework. Section VII shows a simple example of how a Bayesian network could be used to take into account factors related to risk and vehicle position on a freeway. Section VIII extends this approach to Dynamic Bayesian Networks. Finally, Section IX concludes the paper and discusses future work.

II RELATED WORK

Existing driver behavioural models have so far failed to deliver sustainable technology that can reliably predict impaired behaviour such as fatigue (Hartley et al., 2000; Sensation, 2004). This failure is attributed to (i) the dependability of biological markers on broader contextual factors (e.g., perception, individual characteristics) and (ii) the absence of baseline that specifies a normative behaviour. Recently, statistical models have been used to predict driving behaviour. The SmartCar project models and recognize driver manoeuvre at tactical level. It uses HMM (Hidden Markov model) to predict future manoeuvres (Oliver et al., 2000). Kumagai et al., 2003 uses Bayesian network to predict future stop of vehicle at an intersection. Sakaguchi, 2003 also uses Bayesian network to detect unusual driver behaviour. Neural networks and Bayesian networks have been used for building real time recognition of large-scale driving pattern from vehicle dynamics and different classes of driving situation such as highway, main road (Engstrom et al 2001).

Other work uses physiological measures (EMG, EKG) and algorithms such as sequential forward floating selection to detect driver stress (Healey 2000) or driver hypovigilance (Rakotonirainy 04). Stress, fatigue or hypovigilance are among cognitive state that could influence future behaviour of a driver. Therefore such concepts could be included as factors influencing driver behaviour.

The cited works have not fully exploited integrated contextual information related to the driver, vehicle and environment. Despite the extensive research on context awareness concepts (Dey, 2001), the use of context aware systems in vehicles has not been fully investigated (Olsson, 2003).

III FROM COGNITIVE TO COMPUTATIONAL MODELS

The programming existing cognitive or motivational models into in-vehicle devices is the natural inclination of an ITS (Intelligent Transport System) approach toward predicting driver behaviour in real time. Unfortunately, the subjectiveness of motivational models, make such approach challenging. In order to make this process rigorous and scientific, drivers' subjective perception or cognitive concepts must be mapped into numerical values (e.g. level of risk or motivations). Then an absolute numerical measure which can be used to compare risk perception of different drivers for each situation must be determined. Statistical method could be used as a mean to achieve such a goal. However the validity and objectivity of such approach are questionable. Hence, concepts such as risks depend on too many factors that the assessed participant or the assessor could evaluate or keep track of.

Our approach consists in observing the driver in his/her real driving condition with sensor technology. The observation is a learning process that can improve the prediction capability. We have pointed out in Section I the prevalence of uncertainty in a driving environment. Thus we use Bayesian learning as a form of uncertain reasoning from observations. Bayesian learning simply calculates the probability of the occurrence of an event, given an observation, and makes predictions on that basis.

Driver's cognitive concepts, such as risks, are deduced from various sensors such as the dynamics of the vehicle in a certain situation or physiological measures. Such observations could also be augmented with questionnaire such as Sensation Seeking Scale (Zuckerman, 1979). The observation of the driving condition is classified with statistical tools to create a computational model. Such observations are technically possible due to the advent of sophisticated in-vehicle sensors and context aware systems which can gather and analyse data about (i) the physiological state of the driver, (ii) the behaviour of the driver (iii) the dynamics of the vehicle and (iv) the description of the environment surrounding the vehicle and the driver. We borrow techniques from context-aware systems research community to achieve the observation functionalities.

IV CONTEXT AWARE SYSTEMS

Almost 95% of the accidents on the road are due to the human factors. In almost three-quarters of the cases human behaviour is solely to blame. On European roads, 40.000 persons are killed and 1.7 Million are injured every year. Drivers represent the highest safety risk. Computing assistance can improve situational awareness and reduce drivers' errors. Although context-aware systems have a great potential to save lives and prevent injuries on the road, they have not been integrated to safety critical applications such as cars yet. Concretely, context-aware systems can improve the driver's handling of a car by augmenting the awareness of the cars state (e.g. following distance), the environment (e.g. road conditions), the physiological and psychological state of the driver (e.g. available attention level, fatigue). In this paper we store and classify the behavioural information gathered from the context aware system. The history of behaviour is then used to predict future behaviour.

Context-awareness is a computationally oriented design method which improves the flexibility of autonomous systems. It is a concept which has emerged from pervasive and ubiquitous computing research community. Contextual information of an entity X describes relevant information related to the surrounding environment of X. If X is a user then, a context aware system provides *relevant* information and/or services to the user, the relevancy of information depends on the current user task (Dey, 2001). Such relevant information is used to adapt the behaviour of a computational (autonomous) entity/user.

Context can be modelled as value, attribute and relationships between attributes. The values of attributes are gathered from sensors of from users. Context exhibits a range of temporal characteristics; it is imperfect; it has many alternative representations and its content is highly interrelated (Henricksen 2002). Identifying the relevant attribute is a challenge as the type and the number could vary significantly per situation and per driver and can become an intractable problem.

V FRAMEWORK BASED ON BAYESIAN NETWORK

The Framework we are using to model and predict driver behaviour is shown in Figure 1. A context aware system gathers information about the environment. Sensors are mainly video cameras. Vision based technology is available to observe the shape of the road, traffic, road signage, pedestrians, cyclists or other objects. Vehicle dynamics are recorded with data logger and maps. Driver's motor movement are also mainly recorded with vision based computing mechanisms. Head movement, eye blink, steering grip, visual scanning pattern are among observable behaviour that can be recorded with existing technology. Driver's physiological state could be recorded or deduced (from) with different physiological devices such as Galvanic Skin Response (GSR – skin conductivity), Electrocardiogram (EKG – heart rate), Electrooculograph (EOG – eye movement), Electromyograph (EMG – muscle movement) or accelometer (head movements or arms motor pattern) (Rakotonirainy et al., 2004).

Sensors record the state of a given variable related to the driver, vehicle or environment. The states are fused, analysed and interpreted to create a driving situation also called context. The situation is then fed into Bayesian based machine learning system from which a probability based prediction is deduced from the history of behaviour.

VI USE OF STATISTICAL MODELS TO PREDICT DRIVER BEHAVIOUR

A driver"*manages behaviours sequentially in space and time and it organizes goals, intentionally and anticipatory set, which it maintains or changes as appropriate. It plans, prepare, formulates and oversees the execution of action sequences; it monitors the strategic aspects of success or failure, the consequences (including social) of actions, it applies both foresight and insight for non-routine activities and provides a sustained and motivating level of drive" (Bardshaw , 1995)*

It is virtually impossible to design a computational program which could predict future driver behaviour by taking into account all the complex factors shown above. These factors are not necessarily measurable and are afflicted with uncertainty. Our approach consists of using belief networks such as Bayesian networks to model and predict behaviours. Bayesian methods are used as statistical analysis which can provide a flexible theory for making inferences in the presence of uncertainty. It is an extremely powerful tool to provide general solutions to the problems of noise, over fitting and optimal prediction. Bayesian networks are well suited for modelling the joint probability distribution of the random variables representing the state of the driver and his/her environment. They provide the best framework to model, understand and predict complex systems such as driving.

An accurate prediction of driver behaviour requires an understanding of a large number of conditions (context) which cannot be quantified with individual observational measures, such as recording ocular, traffic flow, and cognitive activities. Therefore relevant contextual information related to the driver, the vehicle and the environment need to be fused and analysed to contextualise an action. These contextualised actions are represented in a Bayesian Conditional Probability Table (CPT). Such contextualisation improves the accuracy of the prediction.

The main advantage of using a Bayesian network is the compactness of the representation of the joint probability distribution of its random variables whenever causal relationships in the problem domain are known. For example if no conditional independence relationship is known about four binary values random variables $X_1, \ldots, X_4$, a table with $2^4 = 16$ entries is needed to represent the joint probability distribution $P(X_1, \ldots, X_4)$. Whereas if we know that

$$P(X_1, \ldots, X_4) = P(X_4 \mid X_3, X_2) \times P(X_3 \mid X_1) \times P(X_2) \times P(X_1) \quad (1)$$

then only $2^2 + 2^1 + 2^0 + 2^0 = 8$ entries are required. Provided a decomposition of the joint probability distribution such as (1) can be given by a domain expert, far fewer experimental data will be needed to estimate the parameters of the CPTs. The decomposition (1) implies that given the knowledge of the values of X_2 and X_3, information about X_1 is irrelevant in predicting X_4. More formally,

$$P(X_4 \mid X_3, X_2) = P(X_4 \mid X_3, X_2, X_1)$$

We can view the variables X_1, X_2 and X_3 as influences (causes) on X_4. Not only, Bayesian networks allow to quantify predictions, like computing the probability that X_4 is true given the value of X_2 and X_3. But, Bayesian networks allow us also to make diagnostics, like computing the probability that X_1 is true given the values of X_2 and X_4 (even if X_3 is unknown). The random variable X_4 could describe some attribute of the driver behaviour, X_1 X_2 and X_3 could describe some attributes of the environment, the vehicle or the driver.

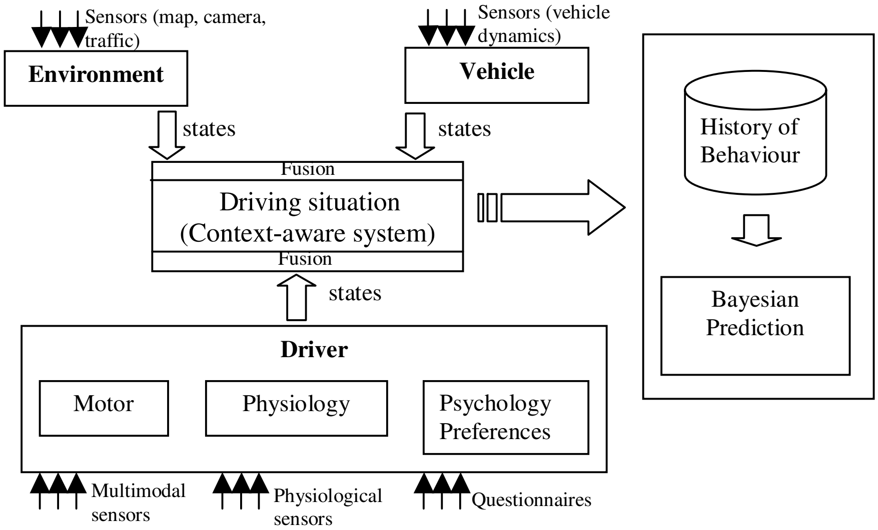

Figure 1: Driver behaviour

VII EXAMPLE: EXIT LANE

This example shows how we can model a simplified scenario in which a driver exits a freeway with Bayesian network. This example combines drivers' cognitive concepts such as risks with vehicles and environmental information such as vehicle position in a lane.

The freeway has two lanes as described in Fig 2. A vehicle on Lane 1, close to the exit will exit the freeway if the driver is willing to take high risk. Otherwise the driver will continue on the same lane.

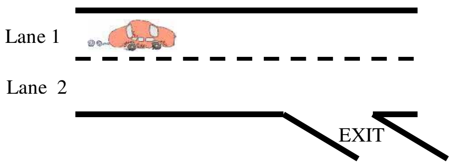

Figure 2: Vehicle exiting a freeway

Age factor as well as the level of alcohol or drug intoxication could influence one's aversion to risk. The Bayesian network associated with the scenario is depicted in Figure 3. Nodes represent quantitative probability information. An arc between a node X and Y means that X has a direct influence on Y. Note that Risk is independent of Lane.

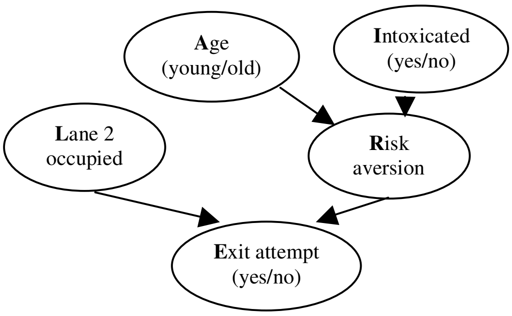

Figure 3: A Bayesian Network for the *freeway exit* scenario

The Bayesian network above factorizes the probability that a vehicle on Lane 1 wishing to exit will actually attempt to exit given the age and state of the driver as

$$\begin{aligned} P(E, L_2, A, I, R) &= P(E \mid L_2, R) \times P(L_2) \times \\ &\quad P(R \mid A, I) \times P(A) \times P(I) \end{aligned} \tag{2}$$

To estimate $P(E \mid L_2 = \text{occupied}, A = \text{old})$, we would need to sum over the possible states of intoxication. That is,

$$\begin{aligned} &P(E \mid L_2 = \text{occupied}, A = \text{old}) \\ &= P(E \mid L_2 = \text{occupied}, A = \text{old}, I = \text{sober}) \\ &+ P(E \mid L_2 = \text{occupied}, A = \text{old}, I = \text{drunk}) \end{aligned}$$

Then we would need to sum over all the possible states of *risk aversion* before being able to use Equation (2).

In this simple example, we hypothesised only two factors for the risk aversion. But, we could refine this model by introducing new random variables. Risk aversion might depends on police presence, on whether the driver is late and on other factors.

VIII EXTENSION TO DYNAMIC BAYESIAN NETWORKS

The time dependency of some random variables follows a Markov process and can be integrated into a Dynamic Bayesian Networks (DBN). A DBN is a Bayesian network that represents a temporal probability model. The Markov assumption states that the current state depends on only a finite history of previous states (Russell, 03). An example of temporal probability is the level of driver-fatigue F_t which increases with time. The random variables F_t take their values in {low, medium, high}. On an hourly time scale, the fatigue can be modelled by stating the values of the $9 = 3 \times 3$ entries of the matrix $P(F_{t+1} \mid F_t)$. DBN can be particularly useful for modelling long journeys of truck drivers. Driver monitoring data could provide the CPT $P(F_{t+1} \mid F_t, R_t)$, where R_t is a Boolean random variable indicating whether or not the driver had a short break during the period t. The random variable F_t can be integrated in the Bayesian Network of Figure 3 on the same level as "Age" and "Intoxicated".

Building a large generic Dynamic Bayesian Network modelling driver behaviour would allow the prediction of the likely impact of policies (compulsory rests for example) on road safety.

IX CONCLUSION AND FUTURE WORK

Fusing contextual information about the environment, vehicle and driver requires large data sets. Data recorded from sensors are unreliable and uncertain. We have described a framework to predict driver behaviour. We have shown that Bayesian network could be used to predict driver's behaviour with certain probability. Such mechanism will be used as a driving assistance mechanism that could detect deviated or abnormal behaviours. This is a preliminary work and we plan to develop methods for automating the process of estimating the parameters of Conditional Probability Table (CPT) from multimedia recordings. We will explore the use of *Dynamic Bayesian Networks* as a modelling tool for situations where the evolution of some random variables can be modelled as a Markov process.

ACKNOWLEDGMENT
This work is partially supported by the Australian Department of Education Science and Training (DEST) and French Embassy in Australia by way of a FAST grant.

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