Reducing driver's behavioural uncertainties using an interdisciplinary approach: Convergence of Quantified Self, Automated Vehicles, Internet Of Things and Artificial Intelligence.

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Abstract: Growing research progress in Internet of Things (IoT), automated/connected cars, Artificial Intelligence and person's data acquisition (Quantified Self) will help to reduce behavioral uncertainties in transport and unequivocally influence future transport landscapes. This vision paper argues that by capitalizing advances in data collection and methodologies from emerging research disciplines, we could make the driver amenable to a knowable and monitorable entity, which will improve road safety. We present an interdisciplinary framework, inspired by the Safe system, to extract knowledge from the large amount of available data during driving. The limitation of our approach is discussed.

Keywords: automated driving, quantified self, internet of things, artificial intelligence

1. INTRODUCTION

Internet of Things (IoT), (semi) automated/connected cars, Artificial Intelligence (Deep Learning) and onboard data acquisition (Quantified Self) are disruptive technologies. They will gradually assist us in performing our daily tasks in safe conditions and will fundamentally revolutionize our interactions with technology.

The driver's unpredictability and their proneness to errors are the main factors contributing to road crashes. There have been many theories and tools, which attempt to model and approximate human behaviour. These endeavours date back to 1949, when Norbert Wiener created the notion of Cybernetics. Cybernetics focuses on how an "entity" such as a driver, processes information, reacts to information and changes to better accomplish its goals. The Cybernetics movement disambiguates human behaviour by using theory of data fusion, communication, control and regulatory feedback. More recently the 'Safe System' framework views the road transport system holistically. It acknowledges that it is not possible to prevent all crashes and aims to prevent or reduce the severity of crashes by minimising the possible role of human error when a crash situation occurs.

The evolution from an unpredictable transport system (e.g. crash, traffic) to an environment where (semi) automated cars are the dominant mobility mean and the driver's behaviour is reasonably predictable is necessary but will take time. There will be many ways in which it will happen. We are still far from being able to eliminate drivers' errors or accurately predict driver's behaviour. Fortunately, the range of possible behaviour in the driving context is actually limited and could be quantified. Most driver behaviour is purposeful – the driver act to efficiently accomplish objectives – rather than completely random. Furthermore, there is a large quantity of untapped data from the environment (IoT), driver (Quantified Self), vehicle (ITS), which can help to model driver behaviour.

The research disciplines, methods and data that we are federating in our framework are:

- Quantified Self (QS): is a movement to incorporate technology into data acquisition on aspects of a person's daily life in terms of inputs (e.g. food consumed, quality of surrounding air), states (e.g. mood, arousal), and performance (mental and physical).
- Internet of Things (IoT) is the network of physical objects—devices, vehicles, buildings and other items, which are embedded with electronics, software, sensors, and network connectivity enabling them to collect and exchange data. IoT data include data from outside of traditional transport, medical care and public health.
- Intelligent Transport Systems (ITS) use information and communication technologies, In-vehicle ITS gather a huge amount of data to assist the driver.
- Artificial Intelligence algorithms such as Deep Learning could be used to analyse/classify the data from QS, IoT and ITS. Deep learning is a branch of unsupervised/supervised machine learning that attempt to model high-level abstractions from data. Using massive and longitudinal data, deep learning could create complex driver behaviour models and predict abnormal behaviour, which could lead to crashes.

The IoT, QS, ITS and cars generate massive amounts of data which can be used reduce driver behaviour uncertainties. The transport community has not considered such data as part of transport applications and researches as it were considered as too big, too complex and too inaccurate. Deep Learning algorithms can curate massive data and extract knowledge to improve road safety. However all this new data, and the Internet-accessible nature of IoT, raise both ethical privacy and security concerns.

The remainder of this paper is organized as follow: section 2 will go into details about each elements of the framework, section 3 will presents the interaction between elements, section 4 will discuss the results and section 5 concludes the paper.

2. FRAMEWORK COMPONENTS ANALYSIS

In this section, all components from the proposed framework: quantified self, internet of things, automated driving and artificial intelligence will be examined to provide a detailed description, examples of their usage in the context of this study and to list drawbacks that may slower the penetration into the market.

2.1 Quantified-self

Quantified self enables the considered system to measure itself its dynamic properties using auto-sensors. This concept, used for decades for biometrics measurements is slowly spreading into other domains such as automated driving. In this study, Quantified-self is defined for a specific system and thus can be generalized to the capacity of the system to auto-evaluate its own properties. This is performed using various sensing technologies depending on what is measured. For a vehicle we might speak about dynamical properties such as vehicle speed and position while biometrics are measured for humans.

When working on the interaction between human and cyber-physical systems, the first application of quantified-self is indeed using biometrics measurements to modify the behaviour of the system. In the case of transportation system, the ADAS behaviour can be changed by using driver and passenger's biometrics. Swan (2015), describes five QS Quantified Self sensor applications that link quantified-self sensors (sensors that measure the personal biometrics of individuals like heart rate) and automotive sensors (sensors that measure driver and passenger biometrics or quantitative automotive performance metrics like speed and braking activity). The applications are fatigue detection, real-time assistance for parking and accidents, anger management and stress reduction, keyless authentication and digital identity verification, and DIY diagnostics. It can be noticed that these application range from human measurements to vehicle measurements. The proposed applications are all direct sensor applications but it is assumed that combining these with the components of the here proposed framework may improve the whole transportation system. Quantified-self will also be introduced under the insurance companies' influence, as providing data results in a subscription discount. Actually, some of these systems are already in-use from driving patterns data logging, low acceleration and low energy use being rewarded, to camera recording to prove innocence in case of accident.

Although quantified-self promises huge improvement in terms of safety, comfort and efficiency, it still raises several issues. Firstly, QS is often an intrusive technology. As an example users of biometrics should often wear different sensors, implying to wear sensors, cable, batteries or other elements to manage. There, the cooperation between human and machine lead to new technologies such as radars installed in driving seats as explained by Vinci *et al.* (2015) and claimed by Faurecia (2015). Secondly, QS implies scrutinizing very personal data such as the heart rate or the respiratory rhythm. This might be a strong drawback if raw data needs to be transmitted to data server for deeper analysis even if existing application of quantified-self already do it such as the Hexoskin (2106) wearable biometrics. Today, the access of these data is not regulated in the same way as GPS position but this will probably evolves when such technology become pervasive.

2.2 Internet Of Things (IoT)

Internet of Things is the way different "things" may interact together using networks and communications. These "things" may include sensors, actuators and networks communications media that, being heterogeneous by nature, can still communicate together. First introduction of Internet Of Things have been found in domotics and assisting living but will rapidly evolves to include industrial, logistics, business and in transportation systems as stated by Atzori *et al.* (2010). The Internet Of Things is made possible thanks to an architecture composed of the sensing, communicating and middleware layers. The middleware layer is software layer linking the object and the application together. Its role is to hide the different object details in order to ease the programmer task.

Within the applications of the internet of things to transportation systems, assisted driving, automated vehicles and communicating cars are the most promising. In these cases, several objects have to be sensed from driver biometrics to vehicle dynamics through infrastructure parameters. A wide range of applications is then possible and Intel (2016) already provided an overview of them and it estimated that data from radar, lidar, cameras and ultrasonics will be more than 1 Gbps. Among all proposed instantiations, several applications are already commercialized such as all ADAS. However, much more can be performed, especially on the automatic map processing. Another example is given in the work of Gerla et al. (2014) where an Internet Of Vehicles is proposed using vehicle to infrastructure communication.

Although, Internet Of Things show promising results, it cannot be a silver bullet on its own as it relies on the objects to be sensed and on the application (sector). When working on the transportation field, as many information are gathered and shared, the data privacy becomes one of the biggest issue. Currently, data generated by vehicles are owned by the car manufacturers or OEMs companies and few are available for the final user. To assist the Internet Of things, data should be opened to users so that the trust in such systems could be restored. Then, there will also be the issues of data quantity and the energy required to store and analyse all these information.

2.3 Automated driving

The driving automation, once synonymous with science fiction, is now expected by the general public as a panacea to solve the problems of road safety, impact of transport on the environment and road congestion. However, major issues related to technology, legislation, ethics and cost still oppose to the mass commercialization.

By definition, the automated vehicle is able to drive alone, without a driver. It is therefore considered a smart object and having capacities of perception, interpretation and action equivalent to that of a human. While several definitions of automated driving exist and a widespread taxonomy about automated driving levels has been providing by the SAE (2014). This taxonomy consists of 6 levels from level 0 where there is no assistance system to level 5 where the driver can delegates all his driving tasks. To achieve these capabilities while ensuring operational safety, all prototypes or existing automated functions currently based on expensive hardware and software redundancy and reduce these costs, expected with the increase of production, not that will be limited as shown by previous experiences in the field of drive-by-wire (no mechanical connection).

Several application of the automated vehicle are already existing, some of them on the market but none of them at level 5. Most of car manufacturers are working on their "automated vehicle" and they claim that it will be commercialized about 2020. If this is feasible for level 3, this is unconceivable for level 5. Then, new actors on the vehicle market appeared in the last decade, the most famous being Google with its automated vehicle having already run millions kilometres. Other actors include, but are not limited to, Uber or NVidia.

Professional fleet will then be one of the main target of the automated vehicle manufacturers, a robotic driver reducing costs compared to a human. It appears, therefore, provided a sufficient level of automation, that drivers of heavy goods vehicles and taxis drivers, ambulances and others will be gradually replaced by their digital counterparts as shown by the investment of companies like Uber. However, such changes will involve a strong social mobilization divisions concerned, and that, more importantly than the VTC could cause recently.

Finally, the automated vehicle fleets will participate in car-sharing and that will provide a new service to transportation users. Public communities will have the necessary investment capacity for the provision of automated vehicles in car sharing. This mode of transport will remain accessible to user demand with a likely cost equivalent to taxis but a controlled availability.

Although automated driving vehicles may solve many problems, it still will induce several issues. Firstly, the legal issue about responsibility in case of accident has to be studied. Secondly, a very controversial issue is the ethics of automated decision in case of ambiguities for an unavoidable event. For example, if the car has to kill the driver of a pedestrian, what will the car choose? Can the car manufacturer determine the algorithm (if possible at all)? This issue has been detailed in the work of Lin (2015). Thirdly, psychological issues may arise from the driver and passenger distrust/overtrust or misuses. Finally several technical issues are still unsolved from adverse conditions driving to the whole system resilience and functional safety.

2.4 Artificial intelligence (AI)

Artificial intelligence is the quality of the system that aims at reproducing human cognitive functions such as learning and problem solving. Artificial intelligence has always been very famous, especially when it can compete with humans. This was the cas with the IBM artificial intelligence Watson who won the Jeopardy TV game. On the same topic, and more recently, Google artificial intelligence AlphaGo who beat the world champion of Go, which is considered to be the most difficult game for artificial intelligence.

Within the field of transportation systems, inside vehicles, artificial intelligence is used for perceiving the surrounding environment, planning trips and commands. The work of Cireşan *et al.* (2012) showed how, by mimicking the neural structure of human brain with neural network, it was possible to efficiently recognize traffic signs. Route and decision planning using artificial intelligence was probably one of the first topic as done in the work of Georgeff and Lansky (1987) where a psychological approach was performed reproducing belief, desire and intention of a real human.

Moreover, applications about analysing data produced by vehicles is now at the centre of all attention. For example analysing data of recurrent trips can be used to predict which route will be taken and then improve routing algorithm. Other applications exist from map enhancement to driver behaviour learning.

One of the most promising branch of AI is the deep learning as detailed in the work of Lecun et al. (2015). This method is part of a broader family of machine learning methods based on learning representations of data which can be unsupervised meaning that is does not need any previous training.

Among all its qualities, artificial intelligence are complex systems requiring expert's capacities to be run. Secondly, the algorithm can rarely be predicted and some undesired behaviour might happen. Considering the safety level required in automated driving, designing it with artificial intelligence may be challenging.

4. FRAMEWORK PROPOSAL

The main purpose of this interdisciplinary framework proposal is to overcome most of the drawback of its

component by combining them. While all research and developments are being done in a very specific field, the components are being improved one by one, sometimes by introducing a part of another. The main objective of this framework is to provide a methodology to help in predicting the driver behaviour in order to improve the whole transportation system. Furthermore, this framework should help researcher and engineers in designing transportation systems using a global approach in order to maximize their system efficiency.
The basic idea of this framework is to decompose the global system into three interacting layers as illustrated in Figure 1.:

- The data layer where all data from sensors and subjective data are collected and merged using data fusion techniques.
- The model layer where the driver behavioural model is constructed to enable predictions.
- The systems layer where existing hardware and software are used to gather or convey information.

Figure 1 is centred on the driver and seeks to predict and control human behaviour.

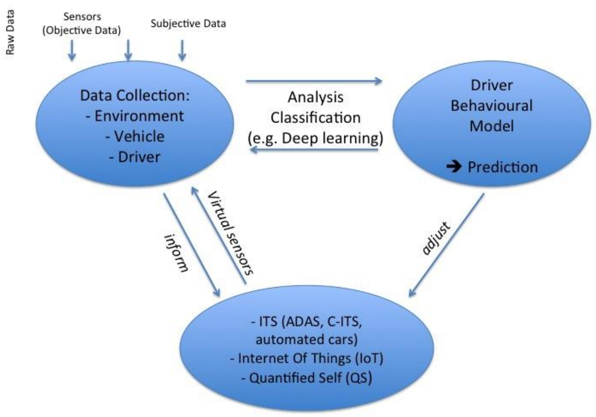

Fig. 1: Data analysis Framework

In this framework, data collected by sensors are defined as objective data and data collected from human (through HMI for example are defined as subjective data. This data are classified or analysed using AI methods such as deep learning to build the driver behavioural model.

The behavioural model predicts the actions of the driver by taking into account the input data as classified by the artificial intelligence algorithms. The behavioural model is a computational framework allowing to predict driver's behaviour in a particular driving situation. The driving situation relates to the environment (e.g. road), vehicle (e.g. speed) or driver (e.g. alertness level). The computational driver behaviour model could be considered as a continuous controller assessing and predicting driver's performance. Then, the results of this layer provide a feedback to the data layer as a real human would do. Results from the behavioural model are used as an input of the physical layer in order to adjust and control them.

The physical layer with hardware and software receive information from the data layer about the environment. Internet Of Things and Quantifies Self then provides sensor outputs to the data collection layer. Automated vehicles are then controlled from the driver behavioural model (incl. ethics and law).

5. DISCUSSIONS

This paper presented a global interdisciplinary framework consisting in interaction between Quantified Self, Internet of Thing, automated driving and artificial intelligence in order to predict the driver behaviour.

There is a conventional discourse in favor of interdisciplinary research. This framework aims at feeding reflexion on the conditions in which transport research could evolve to benefit our society. One of the most longstanding interests of road safety has been the representation of our understanding of the driver and the associated construction of driver behavior model to predict errors and crashes by taking into account the environment, the vehicle, the road and the psycho-social context of drivers. This framework has the advantage of providing a holistic approach to the transportation system as guided by the Safe system. However, it still raises the issue of system complexity and scalability without providing any computational solution. When a system is complex it should be resilient to any perturbation, i.e. the system has to be stable.

6. CONCLUSIONS

Driving is a complex multitasking activity which is very hard to predict due to the fluidity and interactions of the driving factors determining the driver performance. The proposed framework exploits artificial intelligence, quantified self, internet of things and automated driving in order to build a computational driver behavioural model which will reduce the uncertainty of a driver behaviour prediction model. This model can then be used monitor, predict and control a transportation system. Future studies should focus on the resilience and sustainability of such a system when deployed on a large scale in a complex systems.

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