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Psychophysical fitness to drive: possible new methods of monitoring drivers under the influence of psychoactive substances, by means of artificial intelligence systems

L'idoneità psico-fisica alla guida: possibili nuovi metodi di monitoraggio dei guidatori sotto effetto di sostanze psicoattive, tramite sistemi di intelligenza artificiale

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Drivers' fitness is one of the main requirements for a safe driving: it is affected by the consumption of psychoactive substances, both legal (medicines, alcohol) and illegal (drugs) which are relevant factors for traffic accidents. While alcohol tests are now currently used by road patrols, affordable roadside tests for assessing driver's performance and cognitive load, physical fatigue and reaction time are still missing and at the present law enforcement authorities have no effective countermeasures to combat driving impaired by medicines or excess fatigue. The adoption of Machine Learning techniques applied to the data provided by the on-board car system can provide a noticeable support to the detection of driving impairment by road patrols; such objective can be achieved through a fully unobtrusive behavioural sensing system, by using the on-board intelligence already existing in the current vehicles, but without any obtrusive device neither any task overload for the driver. The concept is based on a set of physical data directly measured by a specific small device placed in the vehicle and elaborated by a specific behavioural function; a "normal behaviour" profile (meaning e.g. some upper and lower thresholds of the parameters inside the behavioural function, as well as more sophisticated performance indicators) will be defined after a "learning" period of six months of ordinary driving. When the system has profiled the user, the daily behaviour will be compared with the normal profile and the system will be able to detect deviations from the "normal" profile and to associate such deviations to the most probable cause: psychoactive substances, Alzheimer, fatigue and other impairments. Road patrols, by reading the data of the in-vehicle system, will have in real time an overview of the drivers' status and will be able to address only those presenting problems. This paper explains the status of the research, the exploitation opportunities and the current barriers.

Key words: Physical fitness, Road safety, Machine Learning techniques

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La condizione psico-fisica dei conducenti è uno dei requisiti principali per una guida sicura: questa è influenzata dal consumo di sostanze psicoattive, sia legali (medicinali, alcol) che illegali (droghe) che costituiscono fattori rilevanti per gli incidenti stradali. Mentre i test sull'alcool sono attualmente utilizzati nei controlli stradali, non vi sono ancora test che possono essere effettuati rapidamente durante un controllo su strada per valutare le prestazioni del conducente, il suo stato cognitivo, l'affaticamento fisico e il suo tempo di reazione. L'adozione di tecniche di Machine Learning applicate ai dati forniti dal sistema di bordo dell'auto può fornire un notevole supporto al rilevamento di problemi di guida da parte delle pattuglie stradali; tale obiettivo può essere raggiunto senza alcun dispositivo invadente né sovraccarico di attività per il conducente. Il concetto si basa su un insieme di dati fisici misurati direttamente da un piccolo dispositivo posizionato nel veicolo ed elaborati da una specifica funzione comportamentale; un profilo di "comportamento normale" può essere definito dopo un periodo di "apprendimento" di circa sei mesi di guida ordinaria. Una volta definito il profilo di guida di un dato utente, il comportamento quotidiano può essere confrontato con il profilo normale e il sistema sarà in grado di rilevare deviazioni e associarle alla causa più probabile: sostanze psicoattive, Alzheimer, affaticamento e altre menomazioni. Le pattuglie stradali, leggendo i dati del sistema di bordo, avranno in tempo reale una panoramica dello stato dei conducenti fermati per un controllo e potranno quindi concentrare la loro attenzione su quelli per i quali risulta uno stato alterato. Questo documento spiega lo stato attuale della ricerca le opportunità di sfruttamento e le barriere esistenti.

***Parole chiave**: Idoneità fisica, Sicurezza stradale, Tecniche di apprendimento automatico*

Introduction

Driving is a complex activity requiring several operational, cognitive, tactical (choice of speed and distance from the other vehicles), and strategic (planning trips) skills. Operational and cognitive skills usually depend on factors like ageing, diseases, and fatigue that are crucial for road safety: an effective assessment of the "fitness to drive" is the main way to reduce road accidents.

The use of psychoactive substances is a relevant factor influencing fitness to drive and consequently road accidents: in Europe, the driving under influence of drugs (DRUID, Alcohol and Medicines) Project, performed in 13 countries in 2006-2011 showed that alcohol (> 0.1 g/L) was detected in 3.5% of the drivers, illicit drugs (mainly cannabis) in 1.9%, and medicines (a limited list including mainly benzodiazepines and some opioids) in 1.4%. While alcohol and illicit drugs were mainly observed in male drivers from Southern Europe, medicines were more prevalent in women. In France, the proportion of persons driving under the influence of alcohol is estimated at 2.1% (95% CI: 1.4-2.8) and under the influence of cannabis at 3.4% (2.9-3.9%) (Martin et al., 2017).

A primary goal of the law enforcement authorities is therefore to ensure practical tools for specific and reliable controls "on the road": drug screening devices are becoming more accurate, but the time of their application during a roadside control (around 8-10 minutes) does not allow an effective screening during the road patrols' workday. A feasible solution is to couple such controls with practical tools is for evaluating driver's performance and cognitive load, physical fatigue and reaction time that can give a first result in real time: this way, patrols' officers can concentrate their efforts on those drivers with an high probability of resulting positive, thus increasing the effectiveness of the controls.

The adoption of Machine Learning techniques applied to the data provided by the on-board car system together with a specific behavioural function allows defining a driver "normal" profile after a learning period of around six months of ordinary driving (average period varying with the driving habit of each subject). Once the driver has been profiled, his daily behaviour is compared with the "normal" profile and deviations can be detected and, to same extent, associated to the most probable cause: psychoactive substances, Alzheimer, fatigue and other impairments. This system can be hosted in a small specific device applied in the car, able to provide data in real time through a simple wireless query by the police patrol, with a noticeable advantage during their roadside random controls: they can leave the drivers resulting without behavioural anomalies and apply the tests only to those drivers the query indicates as problematic.

Background

Driving a car includes multiple complex activities, and driving performance depends on the utilization of both physiological and cognitive properties (Jacobé de Naurois et al., 2019). Driving entails a variety of decisions and actions, which can be divided into three types of driver effort: Strategic, Tactical, and Operational (Michon, 1985). *Strategic effort* involves trip planning, tactical effort involves manoeuvring the vehicle in traffic during a trip and *operational effort* involves split-second reactions that can be considered pre-cognitive or innate, such as making micro corrections to steering, braking and accelerating to maintain lane position in traffic or to avoid a sudden obstacle or hazardous event in the vehicle's pathway.

Hence, the continuing role of the driver raises human factors considerations around the topics such as situational awareness, the development and influence of the driver's mental model, expectations (which are informed by the mental model), driver readiness, transfer of control and skill.

The activities and/or automated routines designed to assess whether and to what degree the driver is performing the role specified for him/her are defined as driver monitoring, that can be performed through the detection of cognitive skills. Driver's common errors are largely correlated to overload, distractions, tiredness, or the simultaneous realization of other activities during both manual and autonomous driving (Allnutt, 1987) (Di Flumeri et al., 2018). In fact, the human performance decrease, and consequently errors commission, are directly attributable to aberrant mental states, such as the mental workload while degrading in overload and loss of vigilance, that are considered two of the most important human factors constructs in influencing human performance (Parasuraman et al., 2008).

Human emotional state represents another relevant factor that may affect driver performances. In-car emotional states have become an emerging and important branch of research within the automotive domain in the last years. Different emotional states can greatly influence human driving performance and user experience. The monitoring and regulation of relevant emotional states is therefore important to avoid critical driving scenarios with the human driver being in charge, and to ensure comfort and acceptance in autonomous driving.

As well as in other human-centred domains such as aviation and industry (Borghini et al., 2014), psychological disciplines have been taken on a considerable scientific importance receiving more and more attention. They have become a fundamental instrument for understanding and interpreting the behaviour of the driver (Bucchi et al., 2012), trying to provide cognitive models in order to predict and avoid unsafe actions as well as to understand the relationship between such unsafe behaviours and different factors related to traffic, road complexity, car equipment and external events. The most frequently adopted techniques in this research field are those based on questionnaires and interviews after large-scale experiments in naturalistic (i.e. real driving) and simulated (i.e. by using simulator) settings.

Several Authors investigated the relevance of driving-related cognitive abilities (e.g. reaction time, attention, perceptual speed, intelligence) in predicting accident proneness and fitness to drive (McKnight and McKnight 1999) (Myers et al., 2000). Driving involves distinct cognitive, perceptual, motor, and decision-making skills: for instance, after placing the vehicle on the road, the driver must constantly survey the ever-changing roadway environment to keep the vehicle in the lane and moving at an appropriate safe speed.

The main cognitive function to be assessed are:

- motor speed/reaction time: the speed with which a person/driver can respond to a stimulus/event. It represents how quickly a person reacts to a change in the environment. Reaction time includes the time taken for cognitive processing and the motor response (Summala, 2000).
- perceptual speed: It represents the speed of visual processing. Studies have shown that perceptual speed plays a key role in a person's ability to drive safely (Owsley, 1998). A failure in adequate visual scanning of the field of view is a common cause of crashes or of sudden manoeuvres to avoid a crash.
- flexibility: executive functions concern those processes that control and regulate thought and action (e.g., shifting, inhibition). Executive functions are thought to be play a key role in driving (Adrian et al., 2011), especially when the driver has to deal with dynamic traffic situations (e.g., by switching constantly between different activities essential for safe driving such as verifying and adjusting speed, changing gear etc.).

Among the validated instruments to assess drivers' cognitive abilities, *the Vienna Test System* SCHUHFRIED GmbH is a widely used computerized test battery designed to identify unsafe drivers (Schuhfried, 2005). The tests in the Vienna Test System have been specifically developed for use in traffic psychology and validated for use in traffic psychology. From cognitive-psychological point of view, a generic reaction time is a multi-component cognitive skill dependent on driving conditions and ability, susceptible to learning, subjective risk perception and emotional evaluation.

Reaction time in literature has been mainly studied in relation to the time to stop or time to collision: the diagram in Figure 1 reports the distribution of a driver's brake perception-reaction time, on the basis of a test run on 321 people (Dalla Chiara et al., 2009). The arrows highlight the range of different reaction times adopted by various authors, as a mean value taking into account different physical and psychological conditions of the drivers such as age, health and general fitness. Therefore, drivers' reaction time is a relevant indicator of their fitness.

Existing applications and further developments

Practical applications of driver monitoring are already on the market: Mercedes developed a system called *Attention Assist* (Mercedes-Benz), that observes the driver's behaviour and, at the start of every trip, produces an individual driver profile that is then continuously compared with current sensor data. This permanent form of monitoring is important for detecting the floating transition from awareness to drowsiness and for warning the driver in plenty of time. The system is active at speeds of between 80 and 180 km/h. As well as the speed, lateral acceleration and longitudinal acceleration, the Mercedes system also detects steering wheel movements, use of the turn indicators or pedals and certain control inputs, not to mention external influences such as side winds or road unevenness, for example.

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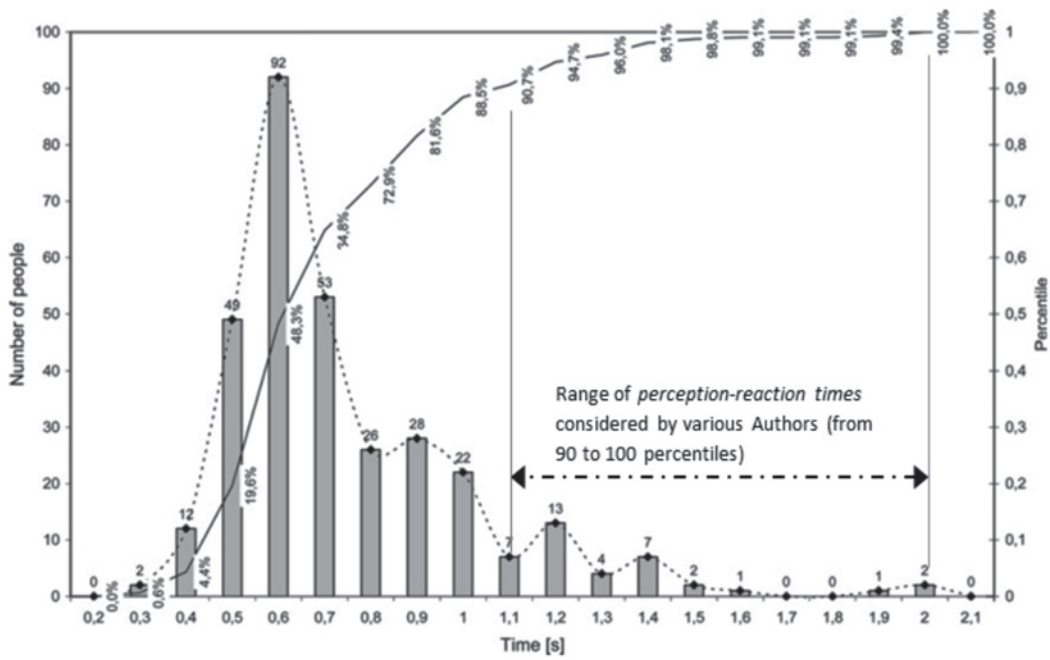

Figure 1.
Drivers' perception and response times and related percentiles.

Observation of steering behaviour has proven to be extremely meaningful as drowsy drivers find it difficult to steer a precise course in their lane. They make minor steering errors that are often corrected quickly and abruptly. Based on these data, the system detects typical indicators of drowsiness and warn the driver by emitting an audible signal and flashing up an instruction on the display in the instrument cluster:

New systems currently studied foresee an in depth profiling during at least six months of ordinary driving, where, a "normal" driving profile produced after the learning period can be compared with any variation through a specific behavioural function, as shown in Figure 2.

After a learning period, the analysis starts with the behavioural function, which contains the key factors that influence safe user behaviour. Since every user is having an own driving style, this behavioural function must be configured to match such individual style and needs a certain learning time. This configuration will be executed automatically during the learning period and the result will be stored as "normal profile". The behavioural function consists of certain indicators (TZ in simple and complex criteria) representing the range of normal driving behaviour for each specific driver: such "normality" will be defined by the self-learning system during a period of ordinary driving. It is clear that different persons in "normal" conditions will have different driver behaviours,

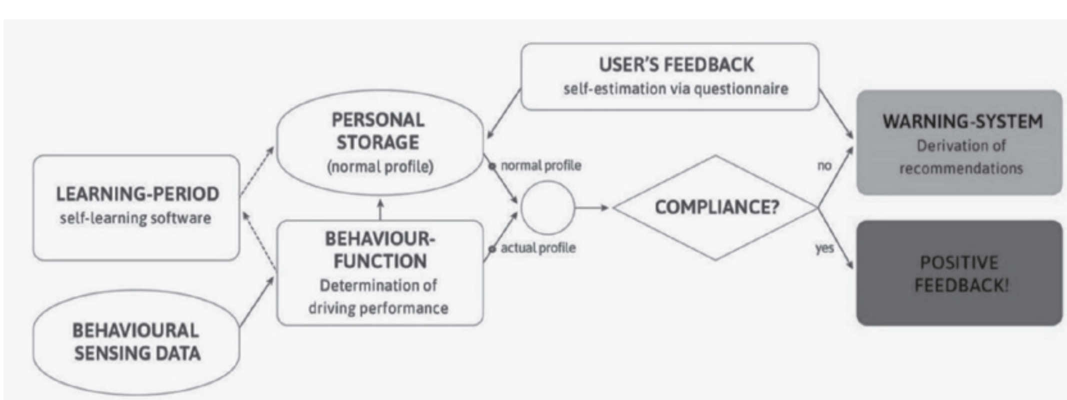

Figure 2.
Functional scheme of the system.

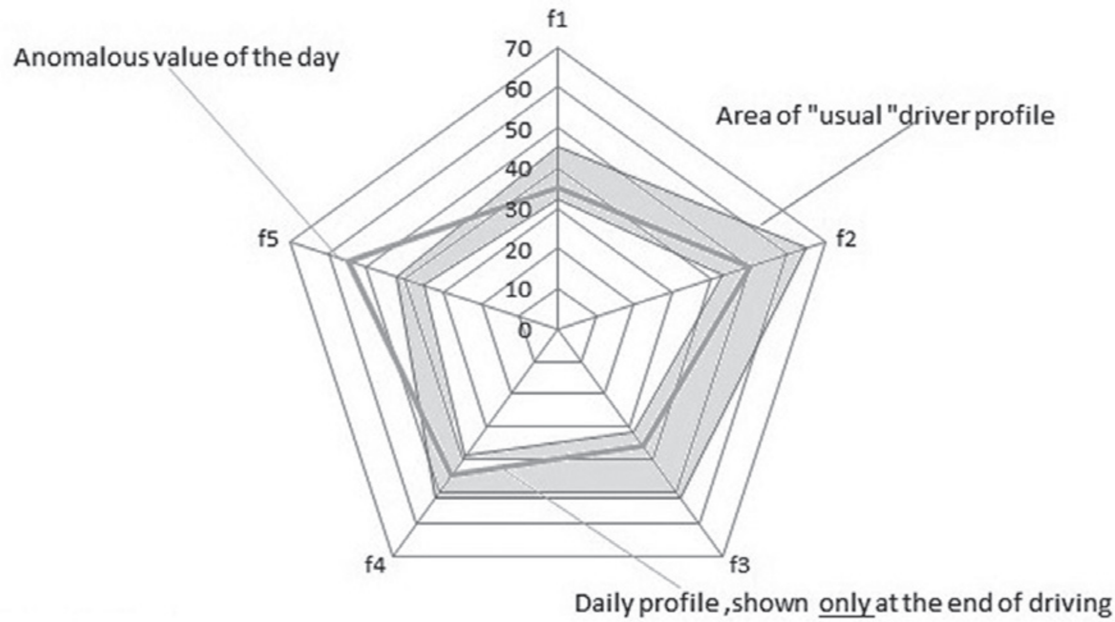

Figure 3.
Example of the driver "normal" profile (dark area) based on 5 parameters and one anomalous value registered by the system.

strictly related to their own characteristics: more or less aggressive, conservative, hesitant etc.

Deviations from normal (within TZ) are determined by the comparison between daily driving results and the personal "normal profile".

Both innovative stages require intelligent algorithms to solve this task. In Figure 3 a simple example is shown to explain the concept of the TZ. In this case each parameter is defined by a TZ indicating the range of normal driving behaviour.

Further efforts are in course in cooperation between engineers and physicians to associate specific anomalous values, like the one related to the indicator F5 in Figure 3, to the most probable causes such as drugs, early Alzheimer fatigue or other cognitive impairments, thus going a step ahead with respect to the systems already on the market.

Once this system is applied in a car, police patrols can query it during a control and know in real time about anomalous values and their probable causes, thus speeding-up the roadside controls and increasing their effectiveness.

Current limits and barriers

From the technical point of view this solution is feasible, with some limits consisting in its architecture: the driver profile is built after a certain "learning" period preliminarily identified in six months of driving; in the quite common case of a vehicle shared by different drivers, there should be a preliminary identification of each driver that is in principle very simple, but very difficult to ensure in the real life. Only the new generation of vehicles with a camera reading the driver's face to detect drowsiness are able to fix this issue, thus excluding the majority of the vehicles currently running on our roads. On the other hand, the system should be able to effectively work in case of professional drivers and particularly trucks, where the driver is clearly identified in each trip.

A relevant barrier is given by the compliance with the data protection regulations: data indicating an anomalous behaviour and its probable causes are sensitive data that should be adequately protected; the roadside control in a stopped vehicle do not present particular issues because the patrol officer can simply put his reading device close to the on-board device. However, the real advantage of the system is with the data put in the cloud, allowing the patrols to know in advance which vehicle should be controlled and therefore enormously increasing the effectiveness. At the present, even with the data duly encrypted, this solution does not appear fully viable.

Conclusions

Driver monitoring is studied since decades and first applications for advising about drowsiness are already on the market; machine learning techniques are able to improve monitoring and detection up to associate drivers' anomalous behaviour to its most probable cause: psychoactive substances, incoming Alzheimer, fatigue and other impairments. This system can be hosted in a small specific device applied in the car, able to provide data in real time through a simple wireless query by the police patrol, with a noticeable advantage during their roadside random controls: they can leave the drivers resulting without behavioural anomalies and apply the tests only to those drivers the query indicates as problematic. This solution can be applied to professional drivers, while the need of an in-depth profiling constitutes at the present a difficult for its wider application. Additional research is needed to ensure an adequate personal data protection, in order to use the system with data stored in the cloud and allow a noticeable increasing of the roadside controls effectiveness.

References

Adrian J, Postal V, Moessinger M, et al. *Personality traits and executive functions related to on-road driving performance among older drivers.* Accid Anal Prev 2011;43:1652-9.

Allnutt MF. *Human factors in accidents*. Br J Anaesth 1987;59:856-64.

Borghini G, Astolfi L, Vecchiato G, et al. *Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness.* Neurosci Biobehav Rev 2014;44:58-75.

Bucchi A, Sangiorgi C, Vignali V. *Traffic psychology and driver behavior.* Procedia-social Behav Sci 2012;53:972-9.

Dalla Chiara B, Deflorio F, Diwan S. *Assessing the effects of intervehicle communication systems on road safety*. IET Intell Transp Syst 2009;3:225-35.

Di Flumeri G, Borghini G, Aricò P, et al. *EEG-based mental workload neurometric to evaluate the impact of different traffic and road conditions in real driving settings.* Front Hum Neurosci 2018;12:509.

Jacobé de Naurois C, Bourdin C, Stratulat A, et al. *Detection and prediction of driver drowsiness using artificial neural network models*. Accid Anal Prev 2019;126:95-104.

Martin JL, Gadegbeku B, Wu D, et al. *Cannabis, alcohol and fatal road accidents*. PLoS One 2017;12:e0187320.

McKnight AJ, McKnight AS. *Multivariate analysis of age-related driver ability and performance deficits*. Accid Anal Prev 1999;31:445-54.

Mercedes-Benz. *ATTENTION ASSIST: Drowsiness-detection system warns drivers to prevent them falling asleep momentarily* (https://media.daimler.com/marsMediaSite/en/instance/ko/ATTENTION-ASSIST-Drowsiness-detection-system-warns-drivers-to-prevent-them-falling-asleep-momentarily.xhtml?oid=9361586).

Michon JA. *A critical view of driver behavior models: what do we know, what should we do?* In: Evans L, Schwing RC, Eds. *Human behavior and traffic safety*. Boston: Springer 1985, pp. 485-524.

Myers RS, Ball KK, Kalina TD, et al. *Relation of useful field of view and other screening tests to on-road driving performance*. Percept Mot Skills 2000;91:279-90.

Owsley C, Ball K, McGwin G Jr, et al. *Visual processing impairment and risk of motor vehicle crash among older adults.* JAMA 1998; 279:1083-8.

Parasuraman R, Sheridan TB, Wickens CD. *Situation awareness, mental workload, and trust in automation: viable, empirically supported cognitive engineering constructs.* J Cogn Eng Decis Mak 2008;2:140-60.

Schuhfried G. *Manual expert system traffic (XPSV).* Mödling: Schuhfried GmbH 2005.

Summala H. *Brake reaction times and driver behavior analysis.* Transportation Hum Factors 2000;2:217-26.