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Evolving cloud-based system for the recognition of drivers' actions

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ABSTRACT

This paper presents an evolving cloud-based algorithm for the recognition of drivers' actions. The general idea is to detect different manoeuvres by processing the standard signals that are usually measured in a car, such as the speed, the revolutions, the angle of the steering wheel, the position of the pedals, and others, without additional intelligent sensors. The primary goal of this investigation is to propose a concept that can be used to recognise various driver actions. All experiments are performed on a realistic car simulator. The data acquired from the simulator are pre-processed and then used in the evolving cloud-based algorithm to detect the basic elementary actions, which are then combined in a prescribed sequence to create tasks. Finally, the sequences of different tasks form the most complex action, which is called a manoeuvre. As shown in this paper, the evolving cloud-based algorithm can be very efficiently used to recognise the complex driver's action from raw signals obtained by typical car sensors.

1. Introduction

The autonomy of the intelligent systems in certain environments also assumes the understanding of actions of other agents in these environments. This is an essential characteristic of intelligent behaviour and an intelligent system. Today, in the era of big data, ubiquitous computing and cloud computing; many different systems exhibit this kind of behaviour, they can recognise the action of other agents. Activity recognition is a widespread and significant research area in ICT. For this reason, considering the focus of the research and the area of application, the research work in this field is associated with terms such as the recognition of plans (Charniak & Goldman, 1993) (Avrahami-Zilberbrand & Kaminka, 2005), user modelling (Webb, Pazzani, & Billsus, 2001), agents modelling (Steffens, 2004), opponent modelling (Ledezma, Aler, Sanchis, & Borrajo, 2009) (Iglesias, Ledezma, & Sanchis, 2009), intention recognition (Sukthankar, Geib, Hai Bui, Pynadath, & Goldman, 2014), behavioural recognition (Candamo, Shreve, Goldgof, Sapper, & Kasturi, 2010), (Iglesias, Angelov, Ledezma, & Sanchis, 2010), etc. In addition, different applications have been developed in this area, such as those related to people care and health, intelligent personal assistants, intelligent user interfaces, electronic commerce and driver modelling (Chen, Hoey, Nugent, Cook, & Yu, 2012; Ke et al., 2013) which is the focus of this work.

Within the area of driver modelling, the recognition of driving manoeuvres raises multiple applications, such as the identification of deficient states of the driver, such as fatigue, distraction, etc., which can cause unsafe driving, by detecting a deviation from his usual way of driving; the creation of cognitive models that allow the reproduction of the way of executing manoeuvres of a human driver in autonomous vehicles; the determination of possible driving styles (normal, aggressive, etc.) that a driver can adopt in certain situations.

Nowadays, the so-called Advanced Driver Assistance System (ADAS) (Bengler et al., 2014) are available in a wide range of vehicles. These systems, whose main goal is to make driving easier and safer, provide a large variety of functionalities such as lane departure warning system (environments-based ADAS) (Cacciabue, 2007) or driver drowsiness detection (Driver-centred ADAS). In particular, an essential aspect of the driver-based ADAS is to detect what the driver is doing or what she/he is going to do. This detection can be done by direct observation, i.e. head-viewing cameras for eye detection (Liu, Xu, & Fujimura, 2002; Sigari, Fathy, & Soryani, 2013; Zhang, Cheng, Feng, & Zhang, 2008) or for yawning detection (Abtahi, Hariri, & Shirmohammadi, 2011; Tiesheng Wang, Pengfei Shi, Wang, & Shi, 2005) and by indirect observation, i.e. sensors (smartphone) in the car (Castignani, Dermann, Frank, & Engel, 2017; Cervantes-Villanueva, Carrillo-Zapata, Terroso-Saenz, Valdes-Vela, & Skarmeta, 2016). Once the drivers

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behaviour is detected, intelligent systems can work as expert co-pilots (Zamora, Sipele, Ledezma, & Sanchis, 2017) and facilitate driving performance and make it easier.

In our approach, a well-established technique for the approximation of complex and non-linear systems is used. Our approach originates from fuzzy modelling, which is one of the most popular methods. Constructing a Takagi–Sugeno model (Takagi & Sugeno, 1985) requires identifying the membership functions and the local model's parameters. Furthermore, if the system is time-variant, the system should have the ability to describe the different behaviours by evolving the model structure and identifying the parameters on-line. In recent years, some evolving identification techniques have been proposed relying on fuzzy logic (eTS by Angelov and Filev (2004), exTS by Memon, Angelov, and Ahmed (2006), FLEXFIS by Lughofer and Klement (2005), switching eTS by Kalhor, Araabi, and Lucas (2013), etc.), that not adapt only the parameters of the model but also the model structure is changed according to the data received.

The simplest form of fuzzy rule-based (FRB) systems was proposed by Angelov and Yager (2011). This new FRB system, named AnYa, uses a non-parametric, vectorized antecedent part. It is based on data clouds, which are sets of previous data samples close to each other, while the membership functions are calculated using the relative data density of the current data with the existing cloud. The data clouds, as the traditional data clusters, are used for partitioning the problem space to detect different operational (non-linear) conditions. In comparison to the data clusters, the data clouds do not require an explicit definition of the membership function (Gaussian, Triangular, etc.). Moreover, the data clouds do not have or require boundaries, therefore they do not have specific shape. The AnYa method can evolve the structure by adding new data clouds. In recent years, the AnYa FRB system was used to solve different control problems (Andonovski, Angelov, Blažič, & Škrjanc, 2016; Angelov, Škrjanc, & Blažič, 2013; Costa, Škrjanc, Blažič, & Angelov, 2013; Škrjanc, Blažič, & Angelov, 2014) and also for identification of different processes (Ali, Hutchison, Angelov, & Smith, 2012; Blažič, Dovžan, & Škrjanc, 2014; Rosa, Gomide, Dovžan, & Škrjanc, 2014).

In our approach, the evolving cloud-based algorithm is used to recognise the driver' action from the signals, which are usually measured in the car. These data are pre-processed and used to form clouds that are typical for different basic elementary actions, which are called atomic actions (*AA*). These atomic actions form more complex prescribed sequences called tasks (*T*). The sequences of different tasks can form a more complex structure, which is called manoeuvre (*M*). As shown in this paper, the evolving cloud-based algorithm can be very efficiently used to recognise a driver's very complex action with the use of the simplest sensors. This paper is organized as follows: after the introduction, the problem description of driver modelling is presented. In the next section, the proposed solution in the form of evolving cloud-based algorithm is given, the pre-processing of the signals, the atomic actions, the tasks and the manoeuvres detection is presented in detail. The experimental results in the learning and in the validation phase are given for the signals obtained on the car simulator. At the end, some conclusions are made.

2. Problem description - driver modelling

Driver behaviour modelling (DBM) is a research problem that has been extensively studied in many different research works Torkkola, Venkatesan, and Liu (2005), Sathyanarayana, Boyraz, and Hansen (2008), Miyajima et al. (2007), Shi et al. (2015) and Nakano, Okuda, Suzuki, Inagaki, and Hayakawa (2009). In Torkkola et al. (2008), a machine learning approach is employed to detect and classify a wide range of driving manoeuvres, to perform a large scale automotive sensor selection and to detect driver inattention by using sensors available in the current vehicle fleet.

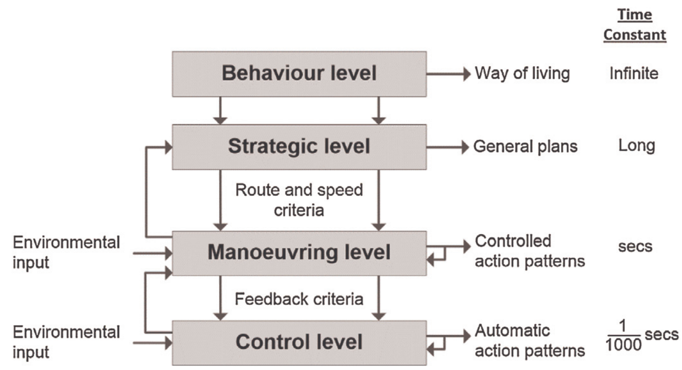

Fig. 1. Different hierarchical levels of the car.

The main goal of DBM is to improve the transport safety and the driving experience. In this sense, there are some surveys that review the literature about this issue. In a recent survey Abuali and Abou-zeid (2016) provide an overview of advances of capabilities and applications, and services of DBM emphasizing research challenges and key future directions. Doshi and Trivedi (2011) survey the field of driver behaviour and intent prediction, with a specific focus on tactical manoeuvres, as opposed to operational or strategic manoeuvres. In Wang, Xi, and Chen (2014) works covering driver skill and different approaches to driver models are presented.

The components and stages involved in driver behaviour modelling are very diverse. In this sense, DBM can be classified as reactive or predictive models taking into account if they classify the observed behaviour or driving manoeuvre in real time or after the action has been conducted. Typically, the predictive models are more difficult to develop than the reactive models. In this research, we present a reactive model. Other aspect in DBM is the hierarchical control model which can be categorized as operational, tactical, and strategic.

In Michon (1985) a hierarchical structure of the road user task is proposed. In that structure, performance is structured at three levels of skills and control which are comparatively loosely coupled: strategic (planning), manoeuvring (tactical) and control (operational). The external outputs of these 3 levels are respectively: general plans, controlled action patterns and automatic action patters. In Panou, Bekiaris, and Papakostopoulos (2007) an adaptation of that hierarchical model is defined and one more level (behaviour level) is included. This level refers to *personal preconditions* and *characteristics*, and has the highest priority because such dispositions heavily influence driving decisions at lower levels. Fig. 1 shows the hierarchical structure of the driving levels.

Other very important aspect are the inputs used in the DBM task. Thus, the vehicle data used can be from the Controller Area Network (CAN), sensors (such radars, lane position sensors, GPS, accelerometers or gyroscopes), or cameras. This research is focused only in the data from CAN.

Due to the complexity of different human activities and the different levels of abstraction that can be used to represent them, it is necessary to establish a taxonomy of activities that allows approaching the task of recognition. Different approaches for creating this taxonomy of activities can be considered (Chaaraoui, Climent-Perez, & Florez-Revuelta, 2012; Moeslund, Hilton, & Kruger, 2006). However, most of these approaches are based on the same idea: defining the taxonomy of actions based on duration, semantic degree and complexity of actions. In this work, an ad hoc taxonomy that consists of different hierarchical levels in a pyramidal form has