Driving Style Recognition for Co-operative Driving: A Survey

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***Abstract*—This paper serves as a critical survey for automatic driving style recognition approaches and presents "work in progress" ideas that can be used for the development of intelligent context-adaptive driving assistance applications. Furthermore, a preliminary specification of a context-adaptive application that can be described by the following three steps is provided: at first, driving style is automatically classified into one out of a set of predefined classes that are learnt through historic driving and trip data; secondly, based on the driving style recognition a context-adaptive driving application is proposed; thirdly, eco-safe and co-operative driving behaviour can be rewarded by the system by introducing a serious game theoretic approach. While the focus of this paper lies on reviewing the state of the art for implementing the first step, providing the high-level specification of the two other steps offers valuable insight on the requirements of such collaborative driving application.**

Keywords- driving behaviour; vehicle dynamics; time-series analysis; supervised learning; classification; co-operative system.

I. INTRODUCTION

Driving is in essence a multi-factor cognition task that can only be perceived in the context of underlying road layout, traffic, weather and social behaviour conditions in a framework where the action of an individual driver is affected by the actions of other drivers and travellers that co-exist temporarily: the driver recognizes the road environment including road layout, traffic conditions, and the behaviour of nearby vehicles, e.g., distance from the vehicle in front, and decides actions to take, such as accelerating, braking, and/or steering. With experience gained each driver develops an individual behaviour behind the wheel, which could impact safety, fuel economy, and road congestion, among other things. For example, a driver, usually, maintains a comfortable time gap to the leading vehicle by adjusting his/her own threshold based on traffic conditions.

Being able to dynamically recognize the driving style is invaluable information for modern Intelligent Transport Systems and Road Operators. More specifically, being able to collect contextual information about the driving style coupled with specific traffic or road characteristics, allows the road operator to perform reasoning about safety characteristics of road usage and react upon that information: for example, Zhang et al. [1] assess vehicle dynamic information and perform a categorization of drivers' acceleration patterns in specific road curves. If this information is compared with speed limit information and accident statistics in the specific road segment under investigation, specific adjustments of the road infrastructure can be proposed in order to minimize the possibility of bad driving behaviour.

Recognizing the driving style is also important in any effective Advanced Driver Assistance System (ADAS) that aims to increase its acceptability by being adaptive to the driver's behaviour: One good example is the Adaptive Cruise Control (ACC) system presented in [1], which adapts its output before entering a curve based on road context data. In contrast with a conventional ACC system that simply maintains the host vehicle speed at a set value if there is no preceding car regardless of the road conditions, the proposed system can provide individual drivers with customized speeds based on their preferred speeds, deceleration rates, and lateral acceleration. Such an adaptive system is expected to increase ride comfort and highly decrease the need for driver intervention in the ACC functionality. More broadly, future ADAS are expected to rely heavily on driving intention recognition and driving behaviour prediction, in order to choose a suitable control strategy to assist and/or warn the driver or even intervene in an automatic manner [2].

Within a collaborative mobility concept, the performance of future ADAS applications can be optimized based on automatic recognition of driving behaviour: for example, the suggested headway, from the vehicle in front, in a co-operative ACC application, can be adapted to the dynamically changing driving style of the driver of the vehicle in front. In a broader consideration, categorizing the driving style of the driver , e.g. as "safe driver", "aggressive driver" or "good fuel economy driver", could be used to encourage community-friendly driving styles; combined with driver records and models of ideal driving style, one's driving style could be compared and used, as an immediate feedback to the driver while driving [3]. In a community building serious game approach, driver coaching and rewarding good driving habits could help promote ecological and safer driving.

In this work, recent approaches that try to automatically identify driving behaviour by recognizing specific car-following and pedal/steering wheel operation patterns will be reviewed in order to identify suitable methods for context-adaptive and collaborative driving applications as these will be investigated within the European TEAM project [4]. Note that approaches that deal with vision-based driver state monitoring (by tracking the driver's face or body motions, see the review of Kang [5]) are not studied here as we want to focus on an inertial base system that enables a discrete, unobtrusive, and seamless recognition of the driver's behaviour.

The structure of this paper is as follows. In Section II, a state of the art review is provided that concludes with observations on the features that appear in the methods under review. In Section III, the functional architecture of a future co-operative driving application that can adapt to the recognized driving style and upon which, a co-operative game-theoretic approach can be built, is presented. Conclusions and ideas for future work are included in Section IV that concludes this work.

II. Methods for Automatic Driving Style Recognition in the Literature

A. *Related Work*

Benavente et al. [6] study three different datasets to examine the relationship between aggressive driving and roadway characteristics, such as type of road, speed limit, number of travel lanes and presence of curbs. Aggressive driving behaviours include speeding, failure to stop, lane violations (such as improper passing), and severe violations (such as operating recklessly). Based on an empirical study on Automatic Cruise Control use by 118 subjects, Fancher et al. [7] classified drivers into five categories: flow conformist, extremist, hunter/tailgater, planner, and ultraconservative. Depending on their velocity and distance from the vehicle in front, a simple empirical model, which divided this two-dimensional feature space into classes of interest by applying rule-based thresholds, was applied. Since such large-scale testing with many different drivers are difficult to be performed while data annotation is too time-consuming and on the other hand real driving styles can vary a lot depending on the country's driving culture and road/weather condition, machine learning methods for discovering patterns and classifying driving styles based on them is highly preferable.

Taking advantage of the recent advancement in machine learning and data mining algorithms, big multi-dimensional time-series data can be explored in order to discover repeating patterns and spatio-temporal relationships among them [8]. Moreover, based on the software/hardware advances in communications and automotive on-board diagnostics units, we are able to record the high-frequency real-time driving information. In this review we are interested in works that discover patterns from rich driving data, which include vehicle signals captured in the context of a specific trip (terrain, weather, traffic information may be included).

In the work of Mudgal et al. [9], speed profiles of different drivers at a roundabout have been modelled, with average circulating speed and non-linear parameter such as position of maximum acceleration determined using Bayesian inference methods. In addition, vehicular emissions were estimated using past experimental data. It is found that speed profiles differ significantly across drivers, as do the mean speeds at the circulating path of the roundabout. The model provides a second-by-second speed profile that can be used for deriving acceleration profile, which can be used for emission hotspots or aggressive driving behaviour recognition. The average circulating speed can also be used as a parameter for developing driving cycles for corridors that include roundabouts. In the work of Spiegel et al. [10], a Singular Value Decomposition bottom-up algorithm that identifies, internally homogeneous, time series segments is adopted. To recognize recurring patterns, the established time series segments were grouped via agglomerative hierarchical clustering. Subsequently, recurring sequences of grouped segments, which can be considered as classes of high-level driving context, can be retrieved.

Spectral analysis of velocity, following distance (only simulation data), gas and brake pedal signals is used for signal representation by C. Miyajima et al. Then, multiple component Gaussian Mixture Models (GMM), applied on a 0.32-s frame length, are used for data modelling. The model fits a GMM for each driver and performs driver identification among a small set of subjects. Targeting at the same driver identification objective, Ly et al. [12] apply automatic extraction and classifications of three simple driving events, defined as brake, acceleration and turn event (GPS positioning data are ignored). Support Vector Machine (SVM) and K-means clustering are compared for a 2-class classification (driver A and driver B), while the classification performance does not exceed 65%.

Johnson and Trivedi [13] detected and classified driving manoeuvres using a smartphone's accelerometer and gyro sensors mounted in the car. In a similar approach, Sathyanarayana et al. applied SVM classification in order to compare the automatic driving maneuver recognition that is based on signals from smart phones against using the CAN signals from the vehicles and equal performance of the two methods is reported.

Amata et al. [15] introduce two prediction models for driving events' recognition: the first is based on multiple linear regression analysis which predicts whether the driver will steer or ease up on the accelerator, or brake; the second predicts driver decelerating intentions using a Bayesian Network. The proposed models predict the three driving actions with over 70% accuracy when the use cases are split into 9 categories of intersection classes. Kishimoto and Oguri [16] also proposed a prediction method that forms an Autoregressive switching-Markov Model (AR-HMM) in order to predict stop probability focusing on a certain period of past movements.

Although not related only with driving style, similar works appear in energy consumption prediction for electric vehicles. In a review of driving behaviour recognition methods for fuel efficiency in hybrid vehicles, Wang and Lukic [17] divide driving styles into three categories: mild drivers (calm driving or economical driving style), normal drivers (medium driving style) and aggressive drivers (sporting driving style). A spine regression model for predicting gasoline consumption rate from speed, acceleration and heading degree information is applied on real driving data (a box-cox transformation to the response variable gives improved modelling) by Nie et al. [18]. Similarly, Quek and Ng [19], train SVM and multinomial logistic regression models but the model is evaluated only for a small set of categories. A last example from the electric vehicles field is the work of Ferreira et al. [20], where a Naïve Bayes classifier was used to classify driver behaviour in several pre-defined classes with respect to electric energy consumption (classes are defined based on percentage of the *state of charge* level decreasing from the ideal driver). As input data, discretized weather information (temperature and raining information), average speed, traffic information, road type, EV age and type, drive mode (work or leisure) and drive period (morning, afternoon, night) were utilized but no evaluation of the method is presented.

Although the majority of the works presented deal with a classification problem, i.e. [9-14][16][20], formulating the problem as a regression problem i.e. [15][18][19], is considered very useful as it gives valuable insights in the recognition problem in hand, by providing estimation of each factor contribution to the event that we wish to recognize.

In all the previous works and independently of the underlying data model (GMMs, Bayesian inference such as HMM) or its absence (SVMs, SVD), a significant correlation of the low-level data being observed and the classes that represent the driver behaviour is assumed. This might be true for classes that represent low-level information such as speed, acceleration or stopping profile, as in [9][10][16], or even some specific manoeuvre detection as in [13 - 15]. However, when higher level behaviour recognition is required, such as driver intention recognition, the existence of contextual information related to the surrounding conditions needs to be taken into account despite the absence of relevant clues. To overcome this problem, Taniguchi et al. [21] assume that contextual information has a double articulation statistical structure. The underlying assumption is that since a concrete value of driving behaviour cannot be easily predicted, an alternative task can be to predict contextual information, i.e., hidden states of these probabilistic models. Following the above line, Fox et al. [22] use an extension of the Hierarchical Dirichlet Process Hidden Markov Model (HDP-HMM), appropriate for dynamic time series modelling, called sticky HDP-HMM. By using this model, the analyser can estimate segments and obtain sequences of hidden state labels (letters) without fixing the number of hidden states. Similarly, in the work of He et al. [23], a double-layer Hidden Markov Model (HMM) is developed for driving intention recognition and behaviour prediction using manoeuvring signals and vehicle state measured by a driving simulator. Each multi-dimensional Gaussian HMM bank in the lower layer corresponds to nine short- braking/acceleration manoeuvres and three steering driving behaviour HMMs while upper-layer multi-dimensional discrete HMMs are built for long-term driving intention in a combined working case. Finally, a semi-supervised time-syntactic pattern recognition approach (by discretizing the values of on-board sensors into simple brake/steering events) is applied for learning models of the driving behaviour of truck drivers by Verwer et al. in [24].

B. Notes on Feature Representation Appopriate for Automatic Driving Style Recognition

Although it is difficult to directly compare the methods presented due to lack of shared common datasets, one element that differentiates this set of methods is the feature representation used. Since this a factor that may judge the power of the overall method, in the followings, we proceed with some observations and we draw some directions for future work in the field.

In terms of driving cycles characteristics, the research has started since as early as 1978 when Kuhler and Karstens [25] introduced 10 aggregate driving behaviour parameters: average speed, average speed excluding stop, average acceleration, average deceleration, mean length of a driving period, average number of acceleration deceleration changes within one driving period, proportion of standstill time, proportion of acceleration time, proportion of deceleration time, and proportion of time at constant speed. More recently, Huang [26] study the influence of 11 parameters on driving cycle recognition and argue that by using 4 of them the prediction result is satisfactory. Higher level features for driving style recognition could be provided if a feedback loop with an advanced driver assistance application is established so that for instance the reaction time from the changing of the signal light to the actual movement of the car is measured, as proposed in [19] and also envisioned in TEAM applications [4].

Feature selection and their representation is critical in the applicability and the discriminative power that a machine learning algorithm can demonstrate for a specific problem in hand. Since the extraction of contextual information for dynamic events like driving requires high computational demanding statistical models (like the ones used in [21-24]) which may not be easily adapted for real-time systems, the robust representation of low-level data is considered necessary since:

- As noted by Liu [27], instantaneous accelerator or brake pedal positions are very noisy signals in the sense that the moment-to-moment position of the pedals do not reveal the actual vehicle speed (due to vehicle dynamics history).
- There is noise in vehicle sensors' measurement and dynamics estimation (even if filtering is applied, e.g., Kalman filter).

While most of the works presented in Section II.A, deal directly with time-series data, without performing a quantization of the signal, there are also some works that choose to work on a histogram-based representation of aggregated data. For example in the work of Ly et al. [12], “histogramming” of the extracted time series vector into 5 bins seems to help: “Using 5 bins histogram reduces the feature vectors size and helps alleviate over fitting when learning with limited data size. Typical signal statistics such as the min, max, mean, and variance are included in the feature vector. Additionally, the duration of the event is also included”. The feature vectors for turning activity recognition include the histograms of both the angular velocity and the longitudinal acceleration. An acceleration/deceleration histogram by fitting a 3rd order polynomial curve to the speed data only at the regions where significant acceleration / deceleration was observed is obtained by Quek and Ng [19].

The advantage of this latter approach is that they can proliferate by the big progress in histogram-based feature vector processing in the fields of text (initially) and image processing where impressive results have been obtained by using a dimensionality reduction technique known as bag of features [28]. A different interesting approach, that handles time-series driving data as a two-dimensional grey-scale image data, has been presented by Griesche in [29]. Converting time-series data into histograms has also been proposed recently by Lin and Li [30] with promising results.

III. A FUTURE APPLICATION: COLLABORATIVE-DRIVING APPLICATION THROUGH GAMING

Gamification can be a solution to the challenge of long term involvement of drivers in cooperative driving. In the agent-based approach of Rossetti et al. [31], the authors focus on driving behaviour elicitation by promoting synergies in a simulated artificial society on a participative basis. In the recently started TEAM integrated European project [32], the goal of the next generation cloud enabled co-operative elastic mobility is pursuit through the development of adaptive transport and driving applications used by a community of users. Part of the preliminary specification work on a Serious Gaming and Community building application which requires a driving style classification component is presented hereafter.

In TEAM, a cloud-based architecture is assumed where intelligent algorithmic components, which are considered as enablers for TEAM applications, run on a distributed cloud server system that also stores local dynamic map information and drivers/travellers history of trips. Moreover, a social network management enabler stores information that the users are willing to share with their co-commuters through smartphones. As a mean of involving the user in a collaborative driving task in order to achieve more fluid and ecological behaviour the TEAM Serious Game and Community Building (SG-CB) application is specified. SG-CB vision is to implement a travelling game based on participation of a community of users where the system provide drivers with “virtual community currency” related with eco-safe driving behaviour (e.g., driver gets a virtual coin if he/she keeps correct headway, he/she can spend the virtual coin later).

The game targets in essence, in coaching the driver towards obtaining a better community performance. For this reason, the SG-CB application should be able to recognize typical driving behaviours such as: headway profile, stopping profile in intersections, longitudinal and lateral acceleration profile. Therefore, a multi-class classification of the driving style that is dynamically updated is proposed as an enabler called “Driving Style Classifier”.

As shown in Figure 1, driving style classification is expected to run online and its output will be assessed by the SG-CB application in order to present to the driver, through HMI, messages relative with the game objectives. The inputs of this component are based on vehicle and context data available from the cloud (like traffic conditions or terrain characteristics based on geo-position). For recognizing different driving styles, several driving indicators are envisioned to be defined using mass past driving data and the classifier will be responsible for assigning a weight corresponding to the similarity of the real time driving event with each of these available indicators.

An appropriate dynamic data representation selected based on the directions derived in section II.B and a robust machine learning algorithm like SVM will be the internal components of the classifier component. For training the classifier, the project plans to create driving reference databases by integrating driving data for safety analysis by previous TeleFOT [33], in European level, and national Tele-ISA [34] and Trafisafe [35] field trials. Using aggregates over these data, driving indicators reference database for highway and urban scenarios will be built. Examples of such indicators are the percentage of kilometres driven at more than 10 km/h over the speed limit, the number of hard longitudinal and lateral accelerations/decelerations, high yaw rate angles, hard braking events per 100km, high acceleration/deceleration combined with rain or darkness conditions per 100km.

IV. CONCLUSIONS AND FUTURE WORK

Requirements and methods for automatic driving style recognition from vehicle and trip data have been studied. Emphasis has been given in the feature selection strategy and a novel promising method for bag of patterns classification, based on time series data turned to histogram-based features, has been identified by combining clues from the literature and the recent advances in the European automotive research projects. Future implementation of a driving style classification module in the terms of a gaming collaborative driving application was drafted based on three categories of driving style: safe, eco-friendly and fluid-promoting in the ACC context.

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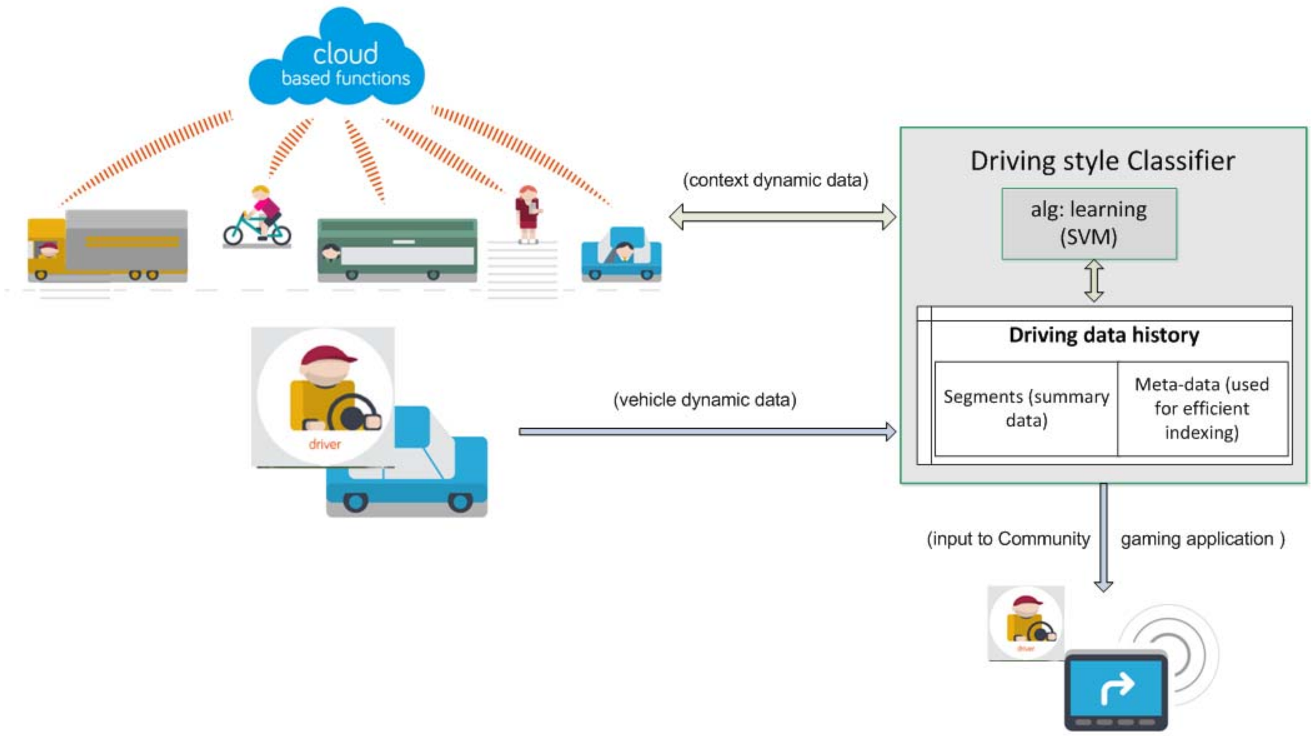

Figure 1: Functional concept diagram for a collaborative driving serious gaming application based on driving style classification