Knowledge-based Reconfiguration of Driving Styles for Intelligent Transport Systems

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***Abstract** - The ceaseless evolution of Information and Communication Technologies (ICT) is reflected on their migration towards the Future Internet (FI) era, which is characterized, among others, by powerful and complex network infrastructures, and innovative applications, services and content. An area of applications that finds prosperous ground in the FI era lies in the world of transportation. In particular, recent and future ICT findings are envisaged to contribute to the enhancement of transportation efficiency at various levels, such as traffic, parking, safety and emergency management. In this context, the goal of this paper is to introduce an Intelligent Transportation System (ITS) that utilizes (i) the driver's preferences, (ii) information extracted from the vehicle sensors, and (iii) previous knowledge and experience, in proposing adaptations of the vehicle's driving style, in an automated manner. Knowledge is obtained through the exploitation of Bayesian networking concepts and specifically the Naïve-based model. Some indicative simulation results showcase the effectiveness of the proposed system, the advantage of which lies in that the reliability of the knowledge-based selection decisions is higher.*

***Keywords** - Intelligent Transportation Systems (ITS), vehicular networks, reconfigurable driving, algorithm, Bayesian*

I. Introduction

Information and Communication Technology (ICT) continue to attract immense research interest [1][2]. Latest trends refer to the migration of ICT towards the era of the "Future Internet" (FI) [3], which envisages mechanisms that promise easier overcoming of the structural limitations of telecommunication infrastructures and their management systems, so as to further facilitate the design, development and integration of novel services and applications [3][4].

An application area that finds prosperous ground in the FI era is transportation. The reason behind this is that automotive vehicles have become an inseparable part of our lives, as they are broadly used in our everyday life. More and more vehicles are sold every year and streets suffer severe traffic jams, especially in large cities, where distances are bigger and consequently, vehicles are even more necessary for transportation purposes. Lately, the automotive world is witnessing a trend related to the extensive use of telecommunications systems inside vehicles. This means that transportation is facilitated by means of newly introduced revolutionary telecommunication techniques and gadgets, which aim to improve either the driver's safety, or the passengers' quality of life through entertainment, or both. The results of such trends are reflected on the term "ITS", which envisages systems that are either related to road infrastructures, making the infrastructure "intelligent", or [1]used inside vehicles traveling on road, attributing vehicles with intelligence [1][2][3][4][5]. By enabling vehicles to communicate with each other via Vehicle to Vehicle (V2V) communication as well as with roadside base stations via Vehicle-to-Infrastructure (V2I) communication, ITS can contribute to safer and more efficient roads. Sensors and sensor networks play a significant part in this effort [17][18][19], as today they are broadly used in passenger vehicles, for safety, as well as emission control reasons. In the future, vehicles will be capable of offering more extensive navigation assistance, monitoring their own systems and behaviour, reconfiguring their operating parameters and alerting the driver when action is required, through sensor systems that will help drivers to cope with hazardous conditions.

With the vision to build on the aforementioned research approaches, the motivation for the work presented in this paper is the fact that several parameters that affect the selection of the appropriate matches among drivers and driving styles, can be changing with time (in a random manner). Therefore, system that can increase the reliability of the decisions is required. The system should provide the probability that the parameters will achieve certain values, based on specific matches.

In the light of the above, this paper contributes to several areas of related work, such as (i) the aforementioned need for development of novel management systems for applications, (ii) the evolution of ITS through proposing a transportation oriented management system attributed with knowledge and experience that can dynamically adapt the vehicle's driving style, and (iii) the enhancement of algorithms used in vehicular networks with knowledge-based principles. The learning functionality is influenced by Bayesian networks [14][15][16][17][18], which constitute robust techniques for modelling and solving stochastic problems, and therefore, are main technologies of future telecommunication systems [19][20][21]. The structure selected in this paper is based on the Naive-based Model [16][17][18]. This model simplifies

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learning by assuming that features (parameters in our case) are independent given the class (selected match in our case).
The structure of this paper is as follows. The next section provides a high-level view of a-drive. Section 3 formulates it mathematically. Section 4 provides some comprehensive simulation results for showcasing a-drive's effectiveness. Conclusions are drawn in the last section (5), where also some perspectives for future work are outlined.

II. Business case and high level description

This section aims at exemplifying the context in which the proposed system is envisaged to operate, through a business case. Moreover, it also provides the system's high-level description.
A set of drivers that may drive a certain vehicle is assumed (in the case of a family, usually one of them is the most frequent driver), as well as a set of driving styles.

Context information
1. Mean driving speed
2. Frequency of turns
3. Mean level of revolutions / minute
4. Frequency of gear changes

(a)

Personal profile parameters
1. Age / experience
2. Gender
3. Mental state/fatigue

(b)

Driving style parameters
1. Vehicle reaction
2. Control
3. Economy
4. Comfort

Figure 1: (a) context information, (b) personal profile parameters, (c) driving style parameters

The drivers and the driving styles are associated with specific parameters, i.e. (a) context information deriving from measurements obtained from the vehicle's sensors (an indicative set of which, is shown on Figure 1(a)), data on the driver's personal profile parameters (depicted on Figure 1(b)), and on the other hand data associated with style related parameters (shown on Figure 1(c)). Last, a set of overarching policies reflects driver/styles preferences, in the form of weights (importance) attributed to the aforementioned parameters.
In general, the manner in which a driver operates the vehicle can change from time to time. This is depicted in a change of the personal profile parameters. Thus, a change in the driving style of the vehicle may be desirable (change of suspension adjustments, gear ratios, speed of vehicle reaction, etc.). The goal of the system is to interact, on behalf of the driver, with all candidate driving styles and find and propose an optimum match. Communication can be guaranteed through the existence of an, easy to deploy, ICT-based management system (such as the one proposed herein – *a-drive*).
The business case assumes that a driver of a vehicle logs on to the *a-drive* system, which may form part of a complete in-vehicle electronic feature that utilizes a Graphical User Interface GUI). In case it is the first time that the user (driver) enters *a-drive*, he is proposed to complete a form regarding the driver's preferences regarding the desirable driving style. *A-drive* then makes some preparatory virtual tests, in order to find the user's most appropriate matches and thus converge faster when needed, as will be shown in the sequel. In the case the user (driver) is already registered, *a-drive* recognizes the user (driver) and has access to his personal information, specific preferences and history. At the same time, *a-drive* is aware of all candidate driving styles and it is in position to find the most appropriate matches. Last, whilst driving the vehicle, a-drive retrieves information from the vehicle's sensors (regarding the mean vehicle speed, etc.) and adapts the driving style appropriately.
In the light of the above, *a-drive* is shown on Figure 2. It uses as input (i) personal profile parameters, (ii) vehicle sensor measurements and (iii) policies which attribute importance to the parameters through numerical weights. The output of the algorithmic functionality is the optimum matching among drivers and driving styles. The solution method follows a phased approach, consisting of (i) the "robust discovery phase" and (ii) the "decision making phase". The robust discovery phase aims at maximizing the probabilities that the parameters will reach certain values, through a Bayesian based model, which helps the system obtain knowledge. The decision making phase steps on those probabilities and finds the optimum matching considering also the importance of the parameters.
It should be also noted that knowledge acquisition is further enhanced by an evaluation procedure, made by the driver concerning driving styles after the completion of a ride. In this respect, parameters are evaluated, at an integers' scale from "1" to "10", in the form of utility volumes [22][22], with "1" standing for "poor" and "10" standing for "excellent". Utility volumes express the level of satisfaction of each driver from the driving style applied. Ranking might concern all available parameters and serves as an input to the Bayesian based model.

III. Formal description

A. Input

The focus is on a driver that drives a vehicle equipped with the *a-drive* system. As already stated, in general terms, the input to the optimum matching (driving style selection) problem consists of context, personal profile, and policies information. These general concepts lead to specific data structures, i.e, the *candidate driving styles*, the *driver's / driving style's parameters*, and the *importance* of each parameter dictated by driver's profile.

The set of the potential vehicle's drivers is PD. D is defined for representing the driver. D can take values 1 to $|PD|$. In the same manner, the set of candidate driving styles is denoted as CDS. DS is defined for representing the driving style. DS can take values 1 to $|CDS|$.

The set of parameters is denoted as N. Each parameter, j $(j=1,...,N)$, can refer to a specific aspect, e.g. mean driving speed, age, gender, etc. Finally, the importance of each parameter, j $(j=1,...,N)$ is indicated by a weight value w_j. In principle, the sum of the w_j weights, over all $j=1,\ldots,N$, will be 1. The w_j values can constitute a vector of weights $\tilde{w}$.

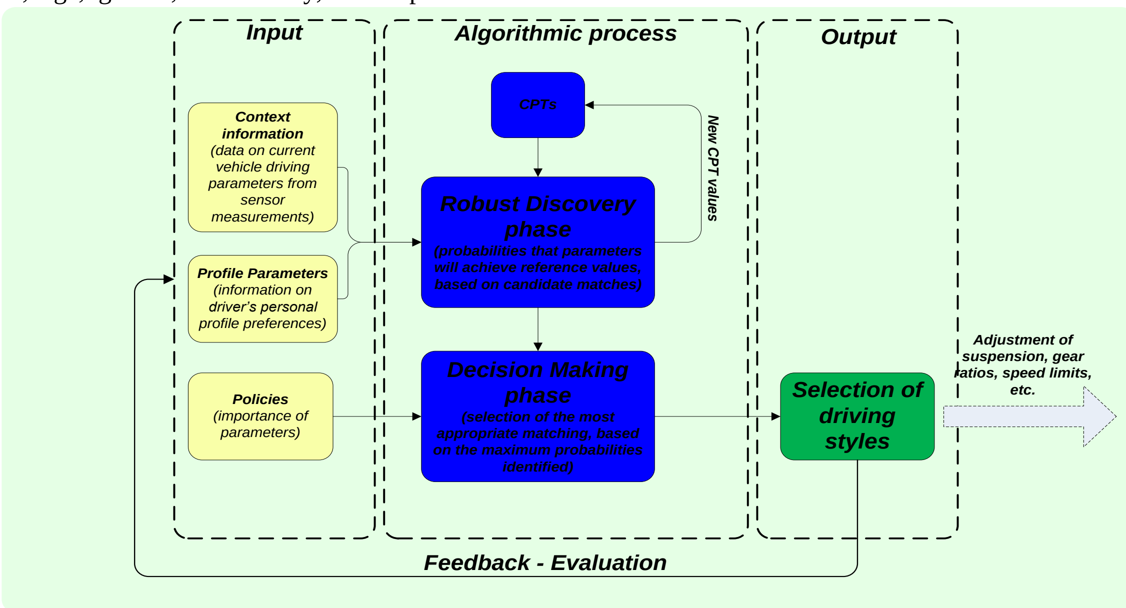

Figure 2: *a-drive* high-level description

As previously mentioned, the parameter values can be changing with time, in a random manner. Therefore, variable i is defined for representing the driving style. Moreover, variable v_j $(j=1,...,N)$ depicts the value of the j-th parameter. Each variable V_j is associated with a set of reference values RV_{ij} $(i \in CDS)$. Variable v_j can take a value among those in RV_{ij}, when driving style i is considered.

The knowledge that needs to be developed relies on conditional probabilities, which have the form $\Pr\left[V_j = rv_{ij}^k \mid DS = i\right]$, where $rv_{ij}^k \in RV_{ij}$ denotes the k-th reference value for the j-th parameter when driving style i is considered.

For each driving style $i \in CDS$, a set X_i can be defined. The members of set X_i derive from the Cartesian product of the RV_{ij} ($j=1,\ldots,N$) sets, i.e., $X_i = RV_{i1} \times RV_{i2} \times \ldots \times RV_{iN}$. Therefore, a member $\tilde{x}$ of X_i has the form $\tilde{x} = \{rv_{i1}^{k1},\ldots,rv_{iN}^{kN}\}$, where $rv_{ij}^{kj} \in RV_{ij}$ ($j=1,\ldots,N$) and k_j ($j=1,\ldots,N$) are integers.

Probability density function. Based on the previous definitions, the following probability density function can be defined:

$$f(\tilde{x},i) = \Pr\left[V_1 = rv_{i1}^{k1},\ldots,V_N = rv_{iN}^{kN}, DS = i\right] = \Pr\left[DS = i\right] \cdot \prod_{j=1}^{N} \Pr\left[V_j = rv_{ij}^{kj} \mid DS = i\right] \quad (1),$$

where $i \in CDS$, $\tilde{x} \in X_i$, $rv_{ij}^{kj} \in RV_{ij}$ ($j=1,\ldots,N$), and k_j ($j=1,\ldots,N$) are integers.

The $\Pr\left[DS = i\right]$ probabilities show the volume of information existing for each driving style i. The sum of the $\Pr\left[DS = i\right]$ quantities, over all $i \in CDS$, is 1. The more information there is on a driving style-i the more reliable the knowledge, and therefore, the higher the $f(\tilde{x},i)$ values.

In general, the values of the $f(\tilde{x}, i)$ function express in an aggregate manner our knowledge on how probable is the achievement of a parameter value indicated in $\tilde{x}$, by driving style i. The sum of the $f(\tilde{x}, i)$ values, over all $\tilde{x} \in X_i$ and $i \in CD$, is 1. In general, the $f(\tilde{x}, i)$ value shows the probability of the ($\tilde{x}$, i) pair, compared to all others possible pairs.

B. Objective and solution

The objective is to select the most appropriate driving style among those in CDS. To do so, the proposed algorithm follows two phases, as previously mentioned, namely (i) the robust discovery phase and (ii) the decision making phase.

Robust discovery phase. The goal of this process is to identify the most probable parameter values. To do so, the probabilities in the right end of (1) need to be updated. For this purpose, *a-drive* collects evaluations made for the CDS driving styles. The update of the conditional probabilities in relation (1) can take into account the "distance" of the collected evaluation values from the reference values. Let us assume that the most recent evaluation indicates that driving style i can achieve rv_{ij}^{coll} regarding parameter j. Let dif_{ij} be the difference between the maximum and the minimum reference value in RV_{ij}. Then, for each reference value, $rv_{ij}^{k} \in RV_{ij}$, there can be a correction factor [17][18]:

$$cor_{ij}^{k} = 1 - \left(\left| rv_{ij}^{k} - rv_{ij}^{coll} \right| / dif_{ij} \right) \qquad (2).$$

Since $0 \le cor_{ij}^{k} \le 1$, a value close to one means that the reference and collected values are close, and thus, that the corresponding conditional probability value should be reinforced accordingly. The opposite holds, if cor_{ij}^{k} is close to zero.

The new conditional probabilities are obtained through the following relation:

$$\Pr\left[V_j = rv_{ij}^{k} \middle| DS = i\right]_{new} = nf_{ij} \cdot cor_{ij}^{k} \cdot \Pr\left[V_j = rv_{ij}^{k} \middle| DS = i\right]_{old} \qquad (3)$$

Parameter nf_{ij} is a normalizing factor for guaranteeing that all the "new" probabilities will sum up to one [17][18]. Moreover, in order to ensure adaptability to new conditions, the conditional probabilities can be prohibited from exceeding a certain threshold, $pr_{\max}$. In summary, the update strategy includes: (i) collection of parameter reference values (through evaluations and measurements); (ii) computation of the correction factors through relation (2), and of the new probabilities through relation (3); (iii) if a probability exceeds $pr_{\max}$ it is set equal to the threshold; (iv) the new normalizing factors are calculated, by forcing the remaining probabilities to sum to (1 – $pr_{\max}$), and the new values are computed for the remaining probabilities.

Decision making phase – exploitation of knowledge. The scheme favors the selection of driving styles that have high probability of achieving the most appropriate parameter values (thus living up to the driver expectations). In order to model these aspects an Objective Function (OF) value, OF_i, is defined for each driving style, $i \in CDS$. The computation of the OF values, OF_i, of all driving styles $i \in CDS$, is made through the following relation:

$$OF_i = \sum_j \left\{ \max(\Pr\left[V_j = rv_{ij}^{k} \mid DS = i\right]) \right\} \cdot w_j \qquad (4),$$

where $i \in CDS$, ($j =$ 1,…, N) and $rv_{ij}^{k} \in RV_{ij}$ denotes the k-th reference value for the j-the parameter when driving style i is considered.

The driving style with the highest OF_i value should be selected based on the knowledge obtained from the aforementioned process. In particular, each driving style corresponds to a specific combination of (a) suspension adjustment, (b) gear ratios, (c) speed limits and (d) steering wheel reciprocation. Thus, the selection depends on the driver's preferences (extracted from the sensor measurements and the profile parameters inserted), as well as on the available driving styles. Finally, the decision is implemented.

IV. Results

The goal of this section is to showcase the behavior of *a-drive*, through studying aspects that include the evolution of conditional probabilities and the OF values.

The scenario used aims at showcasing the gradual development of knowledge and the impact of the continuous change of a driver (who gradually drives more smoothly) on the decision making process. Last, 3 different driving styles are assumed, namely comfort, normal and sport. As mentioned above, each driving style corresponds to a specific combination of (a) suspension adjustment, (b) gear ratios, (c) speed limits and (d) steering wheel reciprocation.

In particular, the scenario assumes that the driver changes his driving behavior, i.e. from a more aggressive one towards a more conservative one. The parameter values (obtained either through sensors or inserted by the driver during the evaluation process) are provided in Figure 4.

Moreover, the parameters' reference values and weights are given in the following figure (Figure 3).

For facilitating the process, it is assumed that 15 computations are split in 3 phases (each one lasting for 5 computations). The second driving style exhibits a better performance in each subsequent phase, implying that it is more suitable.

Parameters	**Reference values**				**Weight**
Mean driving speed	1	4	7	10	$W_{speed} = 0{,}2$
Frequency of gear changes	1	4	7	10	$W_{gear} = 0{,}2$
Mean level of rev/min	1	4	7	10	$W_{rev/min} = 0{,}2$
Economy	1	4	7	10	$W_{\cos t} = 0{,}2$
Comfort	1	4	7	10	$W_{comfort} = 0{,}2$

Figure 3: Parameters' reference values and weights

Parameters	$DS=1$			$DS=2$			$DS=3$		
	1	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Mean driving speed	7	6	5	7	6	5	7	6	5
Frequency of gear changes	8	7	6	8	7	6	8	7	6
Mean level of rev/min	8	7	6	8	7	6	8	7	6
Economy	6	8	9	6	8	9	6	8	9
Comfort	5	7	8	5	7	8	5	7	8

Figure 4: parameter values for the 3 driving styles, split in three phases, namely (1, 2 and 3).

Robust discovery phase.

Figure 5 depicts the conditional probabilities of parameter "economy", likely to be achieved by the second driving style, split in 3 phases. In the first phase which lasts for 5 computations), the conditional probability $\Pr[V_{economy} = 7 \mid DS = 2]$ appears to be the prevalent one. Then, in the second phase (which lasts for computations 6-10), again $\Pr[V_{economy} = 7 \mid DS = 2]$ is the highest one.

However, a slight increase in the values of $\Pr[V_{economy} = 10 \mid DS = 2]$ is observed, with a parallel diminishment of the rest probabilities. Finally, in the third phase (computations 11-15), the most likely reference value to be achieved is 10 and thus $\Pr[V_{economy} = 10 \mid DS = 2]$ gradually becomes the dominant one. There is naturally a point (computation 11) where a false decision may be taken. However, the system quickly "recovers" and thus the small amount of time consumed for knowledge development is a desirable property. It is the time required in order to increase the reliability levels regarding the new capabilities of the second driving style, in terms of achieving a suitability level with regards to the driver desires/behavior.

In this time period the driving style exhibits a "good" behavior. In case the behavior is unstable, the improvement will be considered temporary. The different conditional probabilities will be at low levels, so they will not indicate a clear advantage for any driving style. In any case, however, the amount of time required for the development of knowledge is not large, therefore enabling fast adaptations.

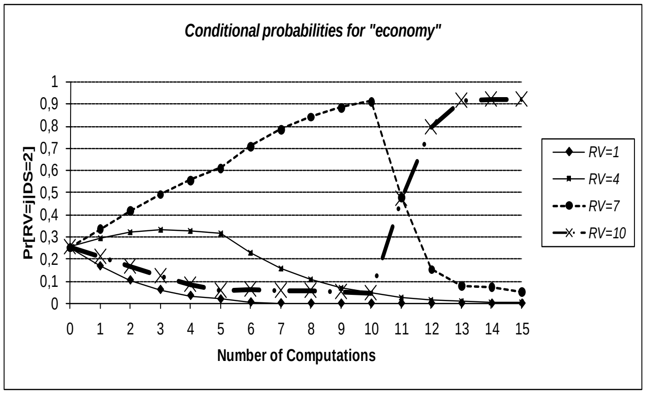

Figure 5: conditional probabilities of parameter "economy" of the 2nd driving style in the 3 phases (the driver is assumed to become more conservative)

Decision making phase.

The OF values of the 2nd driving style reach the highest possible values after around twelve steps on average. These are depicted on Figure 6.

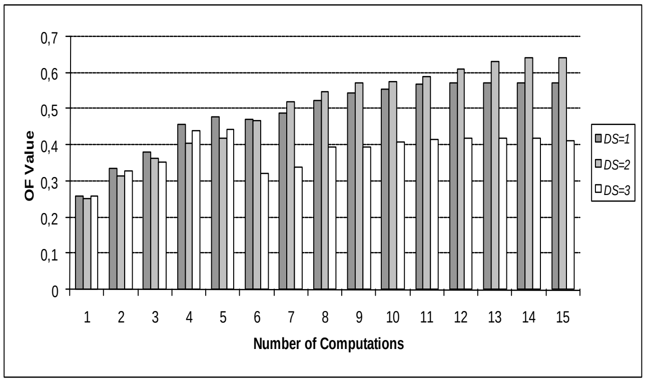

Figure 6: OF values for the 3 driving styles

When possible, the 2nd driving style becomes more appropriate in six steps on average. In general, a small computational effort is required for acquiring the knowledge. This is highly desirable, as it can catch improvements in the behavior of a driver even at a non-permanent basis. The number of steps is not high, and therefore, fast adaptations are possible.

V. Conclusions

Latest trends in ICT refer to their migration towards the FI era, which promises easier overcoming of the structural limitations of telecommunication infrastructures and their management systems, facilitating the design, development and integration of novel services and applications. One important area of applications lies within the area of transportation, mainly by exploiting ICT to benefit drivers and provide several innovative related services. This paper in particular has presented an ITS based on Bayesian networking principles, namely *a-drive*, targeted at exploiting knowledge and experience from past interactions, in dynamically proposing the most appropriate driving style for a driver, whilst driving the vehicle. This is achieved by increasing the reliability of the proposed matches using learning functionality influenced by the Naive-based Model. Apart from the high-level and formal description of the system, the paper has also gone through extensive simulations that showcase *a-drive* behavior. Results show that *a-drive* can (i) adapt to parameter changes fast and successfully and (ii) propose the most suitable driving style whilst driving a vehicle based on knowledge, experience and enhanced decision-making.

This work could be extended by developing further machine learning techniques that could create collective knowledge that would be exploited by *a-drive* more efficiently in reaching the appropriate decisions. Additionally, what could also be investigated is the potential to change the importance (weights) attributed to the parameters during the robust discovery phase and then test the system's response. Part of our future activities shall be also devoted to the integration of the concept of in-vehicle intelligence in larger management functionality for ITS that could exploit several novel concepts, such as issuing directives to the drivers in tackling emergency situations, amending traffic lights and taking other useful decisions during a vehicle's ride.

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