Pervasive Adaptation in Car Crowds

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Abstract. Advances in the miniaturization and embedding of electronics for microcomputing, communication and sensor/actuator systems, have fertilized the pervasion of technology into literally everything. Pervasive computing technology is particularly flourishing in the automotive domain, exceling the "smart car", embodying intelligent control mechanics, intelligent driver assistance, safety and comfort systems, navigation, tolling, fleet management and car-to-car interaction systems, as one of the outstanding success stories of pervasive computing. This paper raises the issue of the socio-technical phenomena emerging from the reciprocal interrelationship between drivers and smart cars, particularly in car crowds. A driver-vehicle co-model (DVC-model) is proposed, expressing the complex interactions between the human driver and the in-car and on-car technologies. Both explicit (steering, shifting, overtaking), as well as implicit (body posture, respiration) interactions are considered, and related to the drivers vital state (attentive, fatigue, distracted, aggressive). DVC-models are considered as building blocks in large scale simulation experiments, aiming to analyze and understand adaptation phenomena rooted in the feed-back loops among individual driver behavior and car crowds.

Keywords: Pervasive Adaptation, Socio-technical Systems, Smart Cars, Car Crowds, Driver-Car Interaction, Vital Context.

1 Car Crowds as Socio-Technical Systems

The term and notion of *socio-technical systems* emerged from the context of labor studies, conducted around the early sixties [1]. Labor studies, generally concerned with the adaptation of humans to organizational and technical frameworks of work or production, analyzed the impact of the *"human factor in industrial relations"*, like e.g. in manufacturing systems proposed by Henry Ford or Frederick Winslow Taylor, and attempted to understand the interrelationship among humans and machines from both the technical (*"efficiency"*) as well as the social (*"humanity"*) conditions of work. A considerable body of research on socio-technical systems emerged as *"organizational development"* (R. Beckhard, MIT Sloan School of Management), addressing the principles and techniques of harmonizing complex organizational work design (*"humanization of work"*) with

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the optimization of productivity. All this research roots on the recognition of the *interaction* between people and technology in the workplace.

More modern socio-technical systems research has looked into the principles and properties of systems considered complex at the confluence of society and technology, particularly the principles and properties that make a system -constituted of many elements that interact to produce "global" behaviour- exhibit a "global" behavior that cannot (easily) be explained in terms of the interactions among the individual elements. More generally, and on a very abstract level, complexity science [2] attempts to better understand systems in which aggregate, system-level behaviour arises from the interactions between component parts in a way that is not straightforward. Such *complex systems* are described as *"... a dynamic network of many agents (which may represent cells, species, individuals, firms, nations) acting in parallel, constantly acting and reacting to what the other agents are doing* where the control *tends to be highly dispersed and decentralized*, and if there is to be *any coherent behavior in the system, it has to arise from competition and cooperation* among the agents, so that the *overall behavior of the system is the result of a huge number of decisions made every moment by many individual agents."*. Conclusively, a complex *adaptive* systems is one in which either (*i*) the number of elements (or parts of the system) and the relations among them are non-trivial (or non-linear), and/or (*ii*) the system has memory or feedback, and/or (*iii*) the relations between the system and its environment are non-trivial (or non-linear), and/or (*iv*) the system can be influenced by, or can adapt itself to a situation or the environment, and/or (*v*) the system is highly sensitive to initial conditions.

In order to study emergent behaviour and phenomena of self organization in complex road traffic scenarios, and following the lines of a socio-technical analysis of the phenomena emerging in traffic, we can assume car crowds as complex adaptive systems (CASs) due to the following observations:

- The interaction among cars in a traffic scenario is seemingly random (since each and every car is following a "local" navigation goal, and the co-incidence of cars happening to come across each other on a certain road is unpredictable), while at the same time seemingly correlated (consider rush-hours, traffic jams or slack periods). The relations among arbitrary two cars in a car crowd is "non-trivial".
- The individual car behavior, as a consequence of the driver behavior, is impacted by memory and feedback. On one hand, routes (and jam escapes) that have been well learned will be repeated until there is an ultimate need to change them (memory). On the other hand, aggressive behaviour exhibited by drivers observably leads to arousal of other drivers, which again can cause aggressiveness (feedback).
- Considering time-of-day, day-of-week, weather conditions, road works or the such as the context [3] (or the "environment") of a car crowd "system", then the effect of such conditions is unpredictable ("non-trivial"). Crowd behaviour in road traffic situations does not change gradually, but changes abruptly after reaching a certain (unpredictable) "critical mass".

– Taking traffic lights as the means with which traffic can be "influenced", we observe "local adaptation" of individual cars/drives (like line-up allegiance phenomena), which at the same time, by completely disregarding surrounding or remote traffic situations, causes "global distortion" (local traffic jams).

With this work we attempt to lay ground for a complex adaptive systems analysis of car crowds, employing simulation based models. We start with models expressing the complex interactions among drivers and vehicles, so called *driver-vehicle co-models* (DVC-models), and arrange them as building blocks in large scale simulation experiments. The ultimate aim of such CAS simulation experiments is to analyze and understand adaptation phenomena rooted in the complex interactions and feed-back loops among individual driver behavior and car crowds in large traffic scenarios (10^5-10^7 entities).

1.1 Driver-Vehicle Co-Models

Modeling the interactions among a driver and the vehicle has to address two major aspects of complexity. First, on the driver side, it has to reflect the complex cognitive task of controlling the vehicle which is built up by four sub-processes (*i*) perception, (*ii*) analysis, (*iii*) decision, and (*iv*) expression (or simply as "chain of sensory perception") [4]. Second, on the vehicle side, data has to be gathered coming from sensors embedded into the car (implicit input), or from the respective controls (steering wheel, pedals, navigation panel, etc. explicit input). A particular difficulty when modeling the driver vehicle interaction loop is the orders of magnitude time discrepancies in the reaction of the driver and the the vehicle. Sensor based data recording, instrumentation, and processing on the vehicle input side, as well as actuator control on the vehicle output side by far excels the human perception-analysis-decision-expression process [5]. Driver Assistance Systems (DAS) have emerged, aiming to improve (power steering) or compensate (ABS breaking) driver performance, but potentially elevate cognitive load at the same time. In addition, on-board entertainment systems can lead to an overload of the visual or auditory channels of perception, again having negative impact onto reaction time. Last, but not at least do vital parameters like fatigue, stress, attention, etc. crucially affect driver performance. All these aspects are essential aspects to be represented in a DVC-model.

As a first approach towards a DVC-model we have therefore focused on the vital state of a driver, and the technological means to continuously collect data so as to be able to compute what we call the *driver vital context* (see Figure 1).

Here the vital context of a driver is an aggregate of information coming from physical sensors, capturing the physiological (heart rate, heart rate variability, skin conductance, body temperature, respiration frequency, etc.) and cognitive (workload, stress, fatigue, etc.) attributes relevant for the analysis of the driver-vehicle interaction loop. In first experiments we have focused on the parameters extractable from an electrocardiogram (ECG)) which are in particular the (*i*) heart rate (RR), (*ii*) heart rate variability (HRV), (*iii*) "autochronic image" (AI) [6] and (*iv*) standard deviation of normal RR intervals (SDNN) as indicated in

Sensor Technology	Sensor Data	Driver Vital Context
Motion	**Respiration**	**“Fatigue”**
Acceleration	Frequency	**“Attentiveness”**
Rotation	Volume	**“Health”**
Speed	**Eyes**	**“Tiredness”**
Strain	Direction	**“Stress”**
Pressure	Blinking Rate	**“Relaxation”**
Electricity	**Skin**	**“Happyness”**
Distance	Temperature	**“Sadness”**
Humidity	Conductivity	**…**
Magnetism	**Body**	
Sound	Motion	
Frequency	EMG	
Volume	Posture	
Radiation	Temperature	
Vibration	**Cardiovascular System**	
Temperature	Blood Pressure	
…	Heart Rate	
	ECG	
	Heart Rate Variability	
	…	

Fig. 1. Computing the driver vital context from sensor data

Fig. 2. The vital context analysis testbed allows to analyze correlations between vehicle-specific data and a driver’s vital context

the fourth column of Fig. 2 (from top to bottom) and have used them in our "vital context analysis testbed" [7] [8] framework to answer questions regarding the interrelationship between a driver's vital context (or "mood") and specific driving situations. A specific source of "mood" indication is the autochronic image (Fig. 2, column 4, third from top), a single feature representing the synopsis of (*i*) mood state, (*ii*) cognitive/mental workload, and (*iii*) activities of the autonomic nervous systems [9]. Much like the heart rate variability (HRV), the AI is frequently also considered as an indicator for the "emotional" state in chronobiology [10].

1.2 A Collective Driver-Vehicle Co-Model

The socio-technical issues we are interested in concerns the feed-back loop originating at the vital (or "emotional") state of a driver, directly translating into his driving style. Perceiving the driving style of other drivers, in turn, influences the emotional state and hence driving style of hte observers. These transitional, yet collective driver state and driving style changes raise global car crowd phenomena like traffic jams, collective aggressiveness, lane blocking, etc.

Often driving style is communicated to nearby cars only, and implicitly [11] as it is being observed by other drivers. A *collective DVC-model*, therefore, needs to reflect this propagation of information within constrained local boundaries appropriately. Diffusion of driver state information to "neighboring" cars, or within field-of-view ranges appears appropriate to address global car crowd phenomena with large scale simulation experiments. Figure 3 sketches the architecture of a complex car crowd model with either centralized or decentralized information management logic. The vehicle-drive interaction loop is extended in the sense that the sensors recognized driver state is propagated into a collective

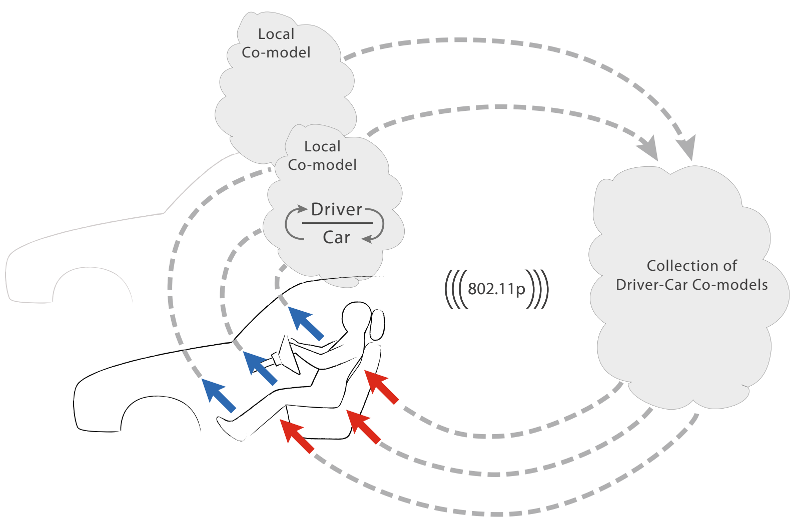

Fig. 3. The collective Driver-Vehicle Co-Model is built from local DVC-models

DVC-model, which in turn generates a flow of control information back to the individual driver.

2 Conclusions and Further Work

Pervasive computing technologies have revolutionized the car driving experience, with significant advances in car steering, breaking and accelerating, etc., navigating, communicating, safety, driving comfort and even entertainment. While most of these advances concern a single driver or a single car, a whole lot of potentials reside in the exploitation of technologies that let spontaneous groups of cars appear as a cooperative crowd (car-to-car communication, car-to-infrastructure communication, remote control, fleet management, etc.). Among the many scenarios that could gain from such technologies are congestion avoidance, traffic shaping, environment protection, energy preservation, power saving, etc.

Car crowds represent, however, cases of complex adaptive systems, in which aggregate, system-level (or global) behaviour arises from frequent and complex (local) interactions between component parts in a way that is "non-trivial". In order to study phenomena emerging from such complex system behavior we attempt for models suitable for simulation based analysis. Particularly for car crowds we propose a driver-vehicle co-model abstracting "local" interactions, and a collective driver-vehicle co-model abstracting "global" behavior. The DVC-model builds upon the driver state and in-car interactions, whereas the CDVC-model expresses cross-car and car-to-infrastructure interactions. Large scale simulation experiments [12] [13] involving these models will gain insight in the mechanism of vehicular pervasive adaptation.

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