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Comparing a multiobjective optimization algorithm for discovering driving strategies with humans

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ABSTRACT

When a person drives a vehicle along a route, he/she optimizes two objectives, the traveling time and the fuel consumption. Therefore, the task of driving can be viewed as a multiobjective optimization problem and solved with appropriate optimization algorithms. The comparison between the driving strategies obtained by humans and those obtained by the algorithms is interesting from several points of view. For example, it is interesting to see which strategies are better. To perform the human versus machine test, we compared the driving strategies obtained by the multiobjective optimization algorithm for discovering driving strategies (MODS) with those obtained by a group of volunteers operating a vehicle simulator. The test was performed using data from three real-world routes. The results show that MODS always finds better driving strategies than the volunteers, especially when the fuel consumption is to be reduced. Moreover, the results show that some volunteers always drive similarly in terms of traveling time and fuel consumption while others significantly vary their driving strategies.

1. Introduction

When a person drives a vehicle along a route, he/she usually optimizes two objectives: the traveling time and the fuel consumption. Vehicle driving by minimizing only the traveling time is quite intuitive and straightforward: the vehicle has to be driven at the maximum allowed velocity all the time. On the other hand, when the fuel consumption has to be reduced, people usually follow some well-known guidelines (Johnson, 2006; Weinger, 2007). However, even if a person follows these guidelines, the optimal driving strategies may not be obtained. To discover how good the human driving strategies are, an optimization algorithm can be designed and evaluated by comparing the obtained driving strategies with the human driving strategies.

An example of an optimization algorithm for this problem is the multiobjective optimization algorithm for discovering driving strategies (MODS) (Dovgan, Gams, & Filipič, 2011; Dovgan, Javorski, Gams, & Filipič, 2011) that we designed and implemented. The algorithm was tested on data from real-world routes and the obtained driving strategies are better than the driving strategies found with previously used optimization algorithms (Dovgan, Tušar, Javorski, & Filipič, 2012), i.e., predictive control (Del Re, Allgower, Glielmo, Guardiola, & Kolmanovsky, 2010) and dynamic programming (Hellstrom, Aslund, & Nielsen, 2010; Hellstrom, Ivarsson, Aslund, & Nielsen, 2009). However, the driving strategies were not compared to the driving strategies pursued by humans.

In this paper we compare the driving strategies obtained by MODS with the human driving strategies. The driving strategies were obtained by simulating the driving on data from real-world routes and minimizing both the traveling time and fuel consumption. To obtain the human driving strategies, an intuitive user interface was implemented and used by a group of volunteers. In addition, the volunteers were classified into categories as expert game players, regular computer users and occasional computer users. Afterwards, MODS driving strategies were compared to the human driving strategies on the individual basis and by taking into account specific categories.

The paper is further organized as follows. Section 2 describes the related work in this field. Section 3 presents the vehicle driving simulator used to evaluate the driving strategies. The MODS algorithm is described in Section 4. Section 5 describes the user interface. Section 6 presents the experiments and the obtained results. Finally, Section 7 concludes the paper with the summary of work and ideas for future research.

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2. Related work

There exist well-known guidelines for obtaining the driving behavior with low fuel consumption. For example, Johnson (2006), Weinger (2007) and other similar sites suggest to drive with a low velocity, to accelerate smoothly with moderate throttle, to shift to higher gears as soon as the desired velocity is reached by skipping intermediate gears, and to avoid braking whenever possible. However, there exist other guidelines for extreme reduction of fuel consumption suggesting that the optimal driving strategy for fuel reduction is the pulse-and-glide driving strategy. Such a driving strategy repeatedly exchanges the acceleration phase (high fuel consumption) and the phase with the throttle valve in a fully closed position (no fuel consumption). The pulse-and-glide driving strategy was used by a team of experts driving for more than 2200 km, establishing an unofficial world record in the lowest fuel consumption (Kroushl, 2005). Lee (2009) demonstrated that the pulse-and-glide driving strategy is better than the driving strategy with a constant velocity, which is in contrast with general guidelines. Although such a driving strategy reduces the fuel consumption, it is not widely used by drivers.

Several researchers studied human driving characteristics. For example, Russell and Norvig (2010) presented a generic learning model which can be used to understand the human driving behavior. The model shows that the driver controls the vehicle in order to follow an intended path using feedforward and feedback control. In addition, the model incorporates the evaluation of the driving, i.e., the errors during the driving. The driver learns during the driving by updating the feedforward and feedback control based on information from the evaluation.

Due to various driving experience and learning capabilities, the driving characteristics vary among the drivers. Canale and Malan (2002) studied how driving characteristics can be determined and how human driving style may be classified by taking into account the start, driving and stop task. The driving styles were identified with a statistical analysis classifying the drivings into a limited number of clusters. In addition, a person classified all the tested drivers based on their behavior as quiet, normal and aggressive. The comparison between the clusters obtained with the statistical analysis and the human classification showed that there is no significant correlation between the two. This fact suggests that the subjective classification is probably limited and therefore not appropriate for driving style classification.

Ossen and Hoogendoorn (2007) studied the driving behavior by analyzing how drivers react to vehicles in front, called leaders, i.e., how they react to changes in the dynamics of the vehicles in front. They empirically analyzed the driving styles of a group of car drivers and showed that they differ considerably. More precisely, clear differences were identified among the speed-dependent distances that drivers want to keep to the vehicle in front of them. In addition, they showed that more than half of the considered car drivers look further ahead than their direct leader and that the number of leaders considered differs between drivers.

The identified driving behavior was used to personalize the adaptive cruise control by several researchers. Fancher, Bareket, and Ervin (2001) proposed both adaptive cruise control and forward collision warning which combine concepts from vehicle dynamics, control theory and human factor psychology. Ioannou and Chien (1993) proposed an intelligent cruise driving strategy using and comparing different dynamic models to describe driver behavior. Nechyba and Xu (1997) used neural network methodologies to describe and adapt human behavior patterns in various driving tasks.

The analysis of the driving behavior can be used also for the purposes other than imitating the human driving. For example, Meng, Lee, and Xu (2006) presented an intelligent vehicle security system which analyzes human driving behavior in order to recognize unauthorized drivers. To that end, the human driving behavior was processed using a hidden Markov model for training human behavior models. The accuracy of driver identification with these models was around 80%, meaning that each person drives in a specific manner significantly different than other drivers.

The previously presented methods focus on learning human driving characteristics and including them in, e.g., adaptive cruise control. However, they do not analyze the quality of the human driving strategies. Nevertheless, they show that human driving strategies differ and that categories of drivers with similar driving behavior can be identified. Unlike the related work that studied only human driving strategies, we compared these strategies with computer driving strategies obtained by the MODS algorithm.

3. Vehicle driving simulator

To evaluate driving strategies, we implemented a black-box driving simulator based on the vehicle description from Lechner and Naunheimer (1999), and Randolph (2007). It receives the control actions (throttle and braking percentage, and gear) for the vehicle, simulates the vehicle driving for one step, and returns the spent time, the consumed fuel and the new vehicle state. The simulation step can be defined either as the route step that has to be simulated, where the length of the step is Δs, or as the time step that has to be simulated, where the duration of the step is Δt. The route step was used by the related algorithms, i.e., the predictive control (Del Re et al., 2010) and dynamic programming (Hellstrom et al., 2010; Hellstrom et al., 2009), and therefore MODS also uses it. On the other hand, the route step is not appropriate for humans since the human reaction is measured in time, not distance. Consequently, the volunteers performed the simulated driving in time steps. After each step, the velocity feasibility is checked. The driving is infeasible if the velocity limit is exceeded or if the vehicle stops.

One step is simulated by taking into account the following forces acting on the vehicle (Lechner & Naunheimer, 1999). Engine moving force F_{EM} is the force produced by the engine when throttle percentage is greater than zero. Engine braking force F_{EB} is the force produced by the engine when throttle percentage is zero. Tire braking force F_{TB} is the force produced by brake pads when braking percentage is greater than zero. Wheel friction force F_W is the force resisting the motion when the vehicle wheels roll on the road. Aerodynamic drag force F_A is the force experienced by the vehicle moving through the air. Tangential component of the g-force F_t is the force acting on the vehicle when the road is inclined. These forces are combined together as follows:

$$F_a = F_{EM} - F_{EB} - F_{TB} - F_W - F_A - F_t, \tag{1}$$

where F_a is the inertial force causing changes in velocity, i.e., changes in vehicle state. The vehicle driving simulator is described in detail in Dovgan et al. (2012).

4. Discovering driving strategies with an optimization algorithm

This section presents the algorithm for discovering driving strategies (MODS) that minimizes the traveling time t and the fuel consumption c.

4.1. Representation of the MODS driving strategies

A driving strategy defines the control actions, i.e., the throttle and braking percentage ε_V, and the gear g_V, for each route step.