

Intelligent Navigation of Autonomous Vehicles in an Automated
Highway System: Learning Methods and Interacting Vehicles Approach

by

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(ABSTRACT)

One of today's most serious social, economical and environmental problems is traffic congestion. In addition to the financial cost of the problem, the number of traffic related injuries and casualties is very high. A recently considered approach to increase safety while reducing congestion and improving driving conditions is Automated Highway Systems (AHS). The AHS will evolve from the present highway system to an intelligent vehicle/highway system that will incorporate communication, vehicle control and traffic management techniques to provide safe, fast and more efficient surface transportation. A key factor in AHS deployment is intelligent vehicle control. While the technology to safely maneuver the vehicles exists, the problem of making intelligent decisions to improve a single vehicle's travel time and safety while optimizing the overall traffic flow is still a stumbling block.

We propose an artificial intelligence technique called *stochastic learning automata* to design an intelligent vehicle path controller. Using the information obtained by on-board sensors and local communication modules, two automata are capable of learning the best possible (lateral and longitudinal) actions to avoid collisions. This learning method is capable of adapting to the automata environment resulting from unmodeled physical environment. Simulations for simultaneous lateral and longitudinal control of an autonomous vehicle provide encouraging results. Although the learning approach taken is capable of providing a safe decision, optimization of the overall traffic flow is also possible by studying the interaction of the vehicles.

The design of the adaptive vehicle path planner based on local information is then carried onto the interaction of multiple intelligent vehicles. By analyzing the situations consisting of conflicting desired vehicle paths, we extend our design by additional decision structures. The analysis of the situations and the design of the additional structures are made possible by the study

of the interacting reward-penalty mechanisms in individual vehicles. The definition of the physical environment of a vehicle as a series of discrete state transitions associated with a “stationary automata environment” is the key to this analysis and to the design of the intelligent vehicle path controller.

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*To all the noble men and the knights fighting the demons
of a binary world in their quest for artificial intelligence.*

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