Dream-like simulation abilities for automated cars

DREAMS4CARS

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Lead Editor	Mauro Da Lio, UNITN		
Contributors	Mauro Da Lio, UNITN		
	David Windridge, Iain Gunn, MU		
	Alex Blenkinsop, USFD		
	All (minor)		
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0.8	21 December 2017	Alex Blenkinsop	Contribution (section 2.3)
1.0	27 December 2017	Mauro Da Lio	Final editing after reviews

Executive Summary

This deliverable describes the first implementation of the Dreams4Cars co-driver agent, which is the basis for the work to be carried out for D3.1 (the first version of the simulation system due at month 18). In parallel, this agent implementation will gradually improve, during the next year, for the final version (D2.2. at month 24).

The current agent (D2.1) implements the biologically inspired architecture which was defined in D1.2: indeed, the release 1 is composed of *a*) the dorsal stream and of *b*) the action-selection loop.

The dorsal stream constructs the equivalent of a “motor cortex”, where peaks of activity encode affordable trajectories/lanes and inhibited regions prevent collisions with obstacles and ensure compliance with traffic directives (traffic lights in this version).

The part of the dorsal stream that produces the active regions uses the same input of the Adaptive agent (sampled curvature profile and vehicle initial state) so that it is interchangeable with it. It is implemented with a neural network that is trained offline. The training input set is created with imaginary lanes, that are generated from few real examples with a first implementation of a dream-like mechanism. The lanes are complemented with randomly generated initial vehicle states. For each training input example, the training output is computed with optimal control. Two slightly different network implementations have been tested. Future versions of the agent may use input data in a different format, in particular occupancy grid-like maps, contributing to both interoperability and preparing for more direct interfacing with raw sensor data such as, e.g., LIDAR and cameras.

The part of the dorsal stream that computes inhibitions for obstacles and traffic lights implements two neural network (one for the longitudinal dynamics and another for the lateral dynamics) that compute the optimal lateral and longitudinal control to comply with the objects. Three network types have been tested for the longitudinal control. The one that performed better, in terms of verification and validation possibilities uses the channel coding approach where arrays of neurons respond to particular intervals of the input and output variables (we have analysed Verification and Validation aspects that, if insufficient, that might hinder the adoption of solutions based on learning). For the lateral control one network has been tested, which uses exactly the same curvature model of AdaptIVe (a down sampled 8-segments piecewise constant curvature model). This network did not perform well in the sense that the neural network did not have any advantage from using 8 constant curvature arcs approximating the lane. Future version of the agent might operate on simultaneous longitudinal and lateral computation of the inhibition, by using obstacle representation such as e.g., co-located geometrical representations in a map for the same goals described for lanes above.

The action-selection loop implements the multi–hypothesis sequential probability ratio test algorithm (MSPRT) that is supposed to be realized in the brain basal ganglia. The algorithm should provide robust action selection. Our tests indicate that a more stable selection is actually obtained when compared to the winner takes all (WTA) algorithm previously used. However, the algorithm may introduce delays when the outcome is unclear. This has been addressed with the introduction of deadline decisions. Future research may involve improving the definition of the salience function in relation to noise (and tuning the thresholds) in a way that situations requiring longer integration are minimized. Furthermore, partial selection (e.g., selecting the degrees of freedom that are already clear without waiting for the whole picture) will also be studied.

The higher levels of the subsumption architecture (Logical Reasoning Module) have also been demonstrated working with an offline scripting mechanism (inline integration is planned as the next step). The subsumption architecture is responsible of steering the agent behaviours to comply with legal requirements (the highway code) and to implement action sequences. The mechanism that has been demonstrated is made of bottom up communication of a symbolic simplified scenario representation and top down communication of legal bounding boxes to bias the action selection mechanism. The actual biasing mechanism is obtained with the modification of the gain matrix used in the MSPRT algorithm. The weights associated to the bounding boxes may be learnt and offer an additional mechanism for learning optimized action sequences that will be addressed in WP 3.6-3.7. Overall the interaction of higher and bottom layers of the dorsal stream via this biasing mechanism re-

sembles the biological biasing solution where immediate less rewarding actions may be biased and selected for a longer-term reward. The mechanism is intrinsically safe because the last say is given to the bottom layer which will never select collision trajectories that are completely inhibited (whatever the biasing gain). Future work with the subsumption architecture may regard then neuralization of the architecture as well as extension to complex road topologies.