CZECH TECHNICAL UNIVERSITY IN PRAGUE

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AGENT-BASED MODELING OF ITS SYSTEMS IN VEHICLE SIMULATOR

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Abstract

TODO

Contents

1 Introduction

In a world in which vehicle transport plays an inseparable role to the society, even with an increasing demand, it is important to analyze and study driver behaviour and inherently interactions and relationships between drivers and their surroundings. This is supported by the fact that, even though substantial advancements in autonomous driving are being made, for the near-future, humans will still have to control vehicles themselves and therefore be exposed to a substantial risk of danger, as data shows that up to 90 % of traffic accidents are a result of human error. [citace] Each traffic accident has got a tremendous effect on socio-economic growth. A study be the European Union states that reduction of X % of traffic accidents could save X euros. [citace] A rather non-cynical point of view is that each life lost is a failure in society itself and effort should be made to diminish fatal accidents.

A method that has proven to be effective at studying driver behaviour and traffic safety is by using interactive vehicle simulators (IVS), which allow to undertake experiments in a safe, controlled and reproducible way. Because driving simulator is basically a digital twin of a real vehicle, it is naturally reasonable to make the interaction between the driver and IVS as close to reality as possible, which inherently improves data quality of the simulation and potentionally also the range of IVS application. An IVS has got a broad spectrum of employment. It is not only used as a tool to research driver behaviour, but also used in development and testing of advanced driver-assistance systems, extending the simulator to a hardware-in-the-loop or a vehicle-in-the-loop system, which enables to test real hardware and simulate full road testing.

Simulating the traffic environment is a complex problem, mainly because of its highly dynamic characteristics. All vehicles need to interact with each other and act upon other drivers' actions. Because agent-based simulations have proven to model complex behaviour well, this modelling technique seems like a suitable solution for achieving a realistic traffic environment for IVS.

The goal of this thesis is to investigate multi-agent systems, their characteristics and evaluate usages of these systems, including applications in the IVS research. Because agent-based systems are also suitable from modelling communication between entities, research regarding application of the agent-based systems in relation to ITS systems, which also share the characteristic of communication and interoperability between individual units within the system, will also be done.

After investigation of ABM in the IVS and ITS field, an experimental work is presented, which shows an implementation of a traffic (ITS) system using ABM, with self-proposed methodology and architecture, which will be described and implemented into an existing IVS. The proposed simulation system will then be examined and evaluated, deciding if the implementation was successful, if the systems adequately represent behaviour observed in real world and possibly performance of the system.

2 Multi-agent systems

Multi-agent systems is a broad paradigm and/or research topic. It is a subfield of Distributed problem solving. A multi-agent systems can be, in a short way, described as a group of autonomous agents that act towards their objectives in an environment to achieve a common goal [1]. The agents can be defined as independent units in an environment, forming a system. They are able to act independently, possess knowledge and communicate with each other (i.e. share the knowledge). The agents should be working towards some form of a common goal, which could be achieved either by cooperating or competing. The agents usually have a perception through which they can gain knowledge from their environment.

The basic definition of MAS suggests that they should be used to model/represent a system that is not-centralized and rather distributed, where autonomous, intelligent units perform actions independently. Multi-agent systems have gained popularity in the recent years, as they offer high flexibility of modelling highly non-linear systems and offering abstraction levels that make it more natural to deal with scale and complexity in these systems [2]. It is apparent that MAS excel in modeling social environments involving humans. MAS share a lot of features with human societies, as these societies also revolve around atomic units - persons, that act independently - each person makes decisions and acts upon their own beliefs. Persons also interact with each other, be it communication, cooperation or competition, while working towards some goal. There are numerous real-life examples that strongly resemble this MAS definition, for example sport teams, where each player has his own role, like a defender and attacker. Although all players have the same intention (i.e. win the game), their specific action differ depending on the state of their environment, each of them acting upon their own beliefs, which makes the team resemble a distributed system. From more practical perspective, MAS paradigm can be used when building air traffic management, for example.

2.1 Agent

Agents are the fundamental building blocks of a multi-agent system. While they can have many features and characteristics specific for their use case and are not possible to generalize, there are several elementary characteristics [1] that define them in scope of MAS.

Situatedness - Agents are designed so that they interact with the environment through sensors, resulting in actions using actuators. The agent should be able to directly interact with its environment using actuators.

Autonomy - Agent is able to choose its actions without other agents' interference on the network.

Inferential capability - Agent is able to work on an abstract goal specifications, identifying and utilizing relevant information it gets from observations.

Responsiveness - Agent is able to respond to a perceived condition of environment in a timely fashion.

Social behaviour - Agent must be able to interact with external sources when the need arises, e.g. cooperating and sharing knowledge.

2.2 Agent type and architecture

As has been already stated, in order to model complex applications, the agent characteristics as well as their internal control architecture will differ between use cases. In an effort to standardize MAS development, several architectures that describe how agents work have been proposed. Generally, there are three classses of agent modelling architectures that are defined based on interaction complexity with external sources:

- Reactive agents
- Deliberative agents
- Interacting agents

An overview of the class characteristics and examples of agent architectures utilizing the respective classes will be given.

2.2.1 Reactive agent architectures

Having first emerged in behaviorist psychology, the concept of reactive agents id founded by agents that make their decisions based on limited information, with simple situation-action rules. The agents usually make decisions directly based on the input from their sensors. This type of agents is mostly suited for application where agent resilience and robustness is the most important factor, instead of optimal behaviour. An example of a reactive agent architecture is the Subsumption architecture.

Subsumption architecture

This architecture described by Rodney Brooks in 1986 [3] and decomposes the agent into hierarchical levels that operate in a bottom-up fashion, meaning that bottom layers that control elementary behaviour are activated by the upper layers that define more complex action or define goals for the agent. It is important to note that the behavioral modules map sensations directly to actions and can only define what the agent does, not being able to change its desires. An example of a subsumption architecture is depicted in fig. 1 with example modules from each hierarchical level, where the bottom-level module is `Avoid Objects`, which is a needed action in order to complete the `Wander Around` action, which can be induced by the general goal on the top layer `Explore World`.

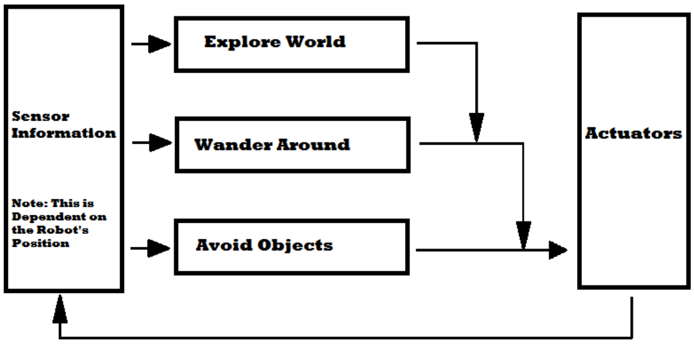

Figure 1: Example of a Subsumption architecture [4]

2.2.2 Deliberative agent architectures

Compared to a reactive agent, deliberative agents have a more complex structure and is closer to a human-like, rational behaviour. A deliberative agent is defined as one that possesses an explicitly represented, symbolic model fo the world, and in which decisions are made via symbolic reasoning [5]. In other words, the agent maintains its internal representation of the external environment and thus capable to plan its actions, while being in an explicit mental state which can dynamically change. The Beliefs, Desires and Intentions (BDI) architecture is the most widely known modelling approach of deliberative agents.

BDI architecture

The BDI paradigm has been used in various applications, such as simulating impacts of climate change on agricultural land use and production [6] or to improve internet network resilience by creating BDI agents that combats DDoS attacks [7]. The main idea behind this architecture is the emphasis on practical reasoning - the process of figuring out what to do. There are three logic components that characterize an agent:

Beliefs - The internal knowledge about the surrounding environment, which is being constantly updated by agent's perception.

Desires - What the agent wants to accomplish. An agent can have multiple desires, which can be hierarchically structured or have different priority.

Intentions - Intentions are formed when an agent commits to a plan in order to achieve a chosen goal. The plans are pre-defined within an agent, formally called a *plan library*. The plan that an agent has set to carry out can dynamically change based on updated beliefs or desires.

These component together define an agent's *reasoning engine* (fig. 2), which drives the agent's (deliberative) behaviour.

This definition can be made clearer with a simple example scenario - a waiter in a restau-

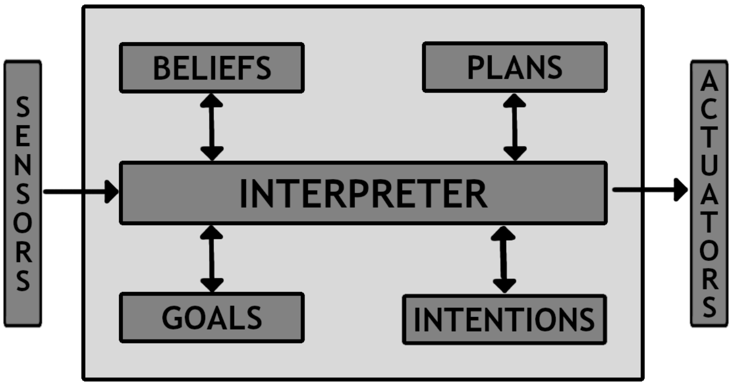

Figure 2: BDI architecture schematic

rant. The waiter's *beliefs* are the tables with customers and information about state of each table (i.e. choosing menu, waiting for meal, willing to pay etc.). The waiter's *desires* are to serve customers, for example accept order from a customer. The waiter carries out his desires by making a plan of *intentions* (e.g. go to table and ask if the customer wants a drink).

This architecture has its advantage in the fact that the functional decomposition of the system is clear and intuitive. However, with this architecture, there is a commitment-reconsideration tradeoff that needs to be optimized [8]. With too much commitment, there is a risk of agent overcommitment, where an agent might be trying to achieve a goal that is not longer valid. On the other hand, if an agent reconsiders too often, there is a risk that the agent will not achieve any goal because it will switch between intentions too quickly.

2.2.3 Hybrid approaches

Hybrid architectures try to utilize the best of both worlds of agent modelling. Purely reactive agents might lack the ability to solve complex tasks, whereas deliberative architectures are challenging to successfully implement on a concrete problem [9]. Pre-compiling a plan library for every possible scenario that can happen in environment with vast amount of complexities is simply not feasible and even impossible, due to uncertainties of following effects when agents affect the environment.

The underlying concept of hybrid architectures is structuring agent functionalities into layers that interact with each other, which provides several advantages, namely *modularization*, which decomposes the agent's functionalities into distinct modules that have determined interfaces, which facilitates design complexity. Furthermore, having distinct layers enables them to run in parallel, thus increasing an agent's computational ability and also reactivity [10].

Generally, amongst the most widely used hybrid architectures, a *controller* layer can be found, which handles reactive tasks therefore is also connected to the sensor readings, and is hierarchically on the lowest level. Then, there are *planning* layers that handle the logic-based, deliberative tasks and often interact with the controller layer. In-between them, there is usually a *sequencing* layer that can suppress output from the reactive layer. An example of a well-known hybrid architecture is the $_3$T architecture, whose abstract model can be seen on the figure (3) below.

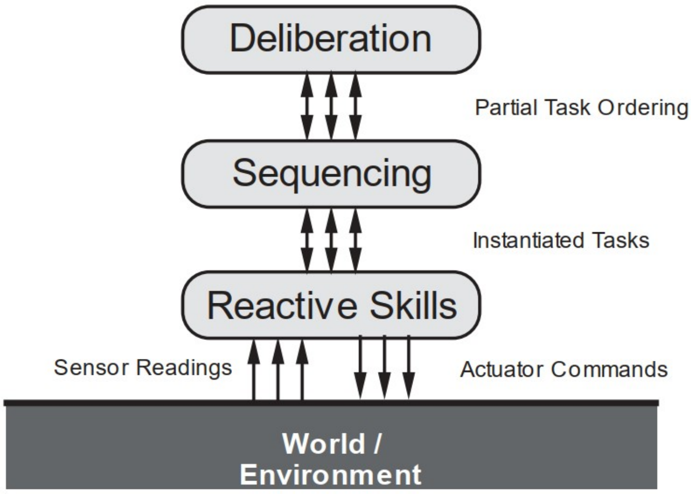

Figure 3: An architecture model of a $_3$T hybrid architecture [11]

$_3$T architecture

This architecture builds upon a predecessor architecture called RAPs (Reactive Action Packages) [12]. A RAP is essentially a process or a description of how to complete a task using discrete steps. Note that it has got no planning abilities, i.e. it's action is only based on current perceived environment state and not on an anticipated state. When a RAP is executed, it should finish only when it satisfied its outcome or else it will produce a failure state. This ensures that the agent can self-diagnose a failure and implement some fail-safe mechanisms. Individual RAPs are queued by the interpreter, in the case of the $_3$T architecture it is called a *sequencer*, which is the intermediate layer between the *reactive skills* and *deliberation* layer.

The skills layer is a collection of so-called *skills*. Skills provide an interface of an agent to its environment. They are its abilities that allow the agent to transform or maintain a particular state in the environment. Each skill has got an expected input and output, which allows to route them together.

Finally, the deliberation layer is responsible for planning on a high level of abstraction, in order to make its problem space small. Routine sequences of tasks should not be specified or dealt with at this layer.

2.3 Interaction between agents

Interacting agents are able to interact with other agents within the environment. This concept extends an agent with an interface dedicated to communication. Agents are then able to directly communicate and thus cooperate in a decentralized fashion. The concept of cooperation between agents is important in the ITS modelling context, as these systems facilitate sharing information in-between drivers and also from the road traffic environment to drivers. Therefore, interaction is a strong component when considering modelling ITS and road traffic in general.

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