An Agent-based Model of Autonomous Automated-Guided Vehicles for Internal Transportation in Automated Laboratories

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Abstract: Agent-based modelling enables simulating complex systems and controlling them, as well. In the industrial domain there are plenty of these systems not only because of the size but also because of the need for fault-tolerance and adaptability. Typically, these cases are solved by dividing systems into different dimensions, including the transportation one. In this paper, we take this approach to build a framework to develop and control transportation in applications within the industrial domain, which will be tested on an automated laboratory. The framework is based on a multi-agent simulator that contains the model of the plant with transportation agents having a multi-layered architecture. The lower-level layers correspond to those that would be embedded into physical transportation agents. Therefore, while agents communicate to each other within the simulator environment, communication between upper-level layers and lower-lever layers of each agent is done internally for the simulated parts and externally for the real counterparts. The simulator can be used stand-alone to functionally validate a system or in combination with real agents as a monitoring/controlling tool. Preliminary results prove the viability of the framework as a design tool and show the difficulties to work with physical agents.

1 INTRODUCTION

The industrial domain is populated with highly complex and demanding applications that also are required to be flexible and robust. Therefore, it has become commonplace to use divide-and-conquer strategies to develop the systems for these applications. For instance, splitting system designs with respect to different aspects of the application, which include the one for internal transportation of material (Schreiber and Fay, 2011).

In this paper, we focus on this aspect to develop a framework in which transport systems for applications in the industrial domain can be designed and further deployed.

These systems are also required to be as efficient as possible. Taking into account that efficiency must include cost of failures and planning changes, it turns out that a robust and flexible system has more chances to be more globally efficient that others that lack these characteristics, possibly because of being centrally controlled. Following this and other similar reasonings, industry has turned to use agents and agent technology to obtain fault-tolerant and adaptable systems.

Our approach resembles that of (Fernández-Caballero and Gascueña, 2009) on complete development environments for agent-based systems and uses an agent-based model (ABM) of the transport system that accepts inputs from the rest of the system and outputs control data for the physical transportation units as well as other data to the system. Differently from their proposal and other works alike, our approach uses a single ABM tool to simplify the development framework and minimize the development costs.

The proposed ABM has a relatively simple architecture (see Fig. 1), that organizes agents into two classes: the one for the external elements (application-related agents, A_j) to the transportation system and the one for the vehicles or *taxis* (agents T_i with links to physical, R_i, and virtual, V_i, lower-level layers).

The model is run under inputs that come from external agents and physical elements and generates outputs for the latter ones. This control loop might be too slow for many applications unless physical

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elements have embedded some controllers and relation with the ABM is done at a higher level of abstraction. However, even with this solution, ABM has to be executed fast enough to interact at real time with the physical elements. This requires agents to be efficient in taking decisions, which usually goes against relexive, ellaborated behaviours and to have simple communication protocols that enable negotiations to occur within a few messages.

In the proposed framework, the model has three use cases: 1) for functional validation; 2) for plant characterization, which includes testing whether real time requirements are met, parameter identification, and controller setup, and 3) as a model for the controller of the transportation system, including a mixed-reality environment for monitoring and supervising in human-assisted operation.

As the framework could not be tested on a real application, it has been tested with a realistic one that could be operated with automated-guided vehicles (AGVs) built on small robots.

For this, we have focused the work on automated laboratories of clinical analyses, as they use relatively simple transport infrastructures in which small AGVs can successfully replace conveyors.

The paper is organized as follows. The next section is devoted to outline the used of agent-based models in the transportation arena and our approach. Section 3 highlights the application in automated laboratories, while the following sections detail the mechanisms for plant characterization and synchronization between the simulator and the real world. The last section concludes this paper by summarizing the contribution of our work and devising short and long term continuation lines.

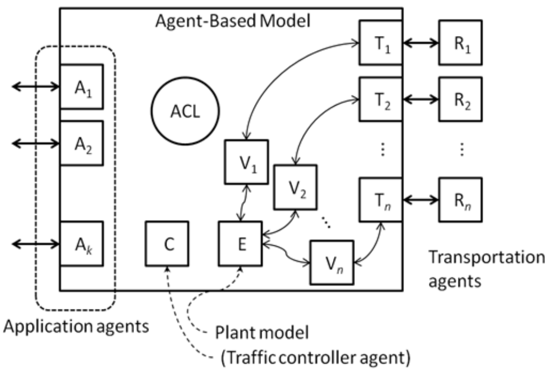

Figure 1: Multi-agent architecture of the transportation system.

2 AGENT-BASED MODELLING

Typically, ABM is used to analyze, via simulation, social behaviour of individuals and how it is affected by changes on individual behaviour, as presented, for instance, by Kashif *et al*. (2011). Additionally, ABMs can be taken as systems models and used to control them by generating the commands to the individuals so that they behave as required by the related applications.

2.1 ABMs as System Simulators

In the review of ABM for transport logistics done by Davidsson *et al*. (2005) it is noted that agents are used mainly to support decision taking but not to automate processes, i.e. not as distributed system controllers.

In fact, as shown in a more recent review by Santa-Eulalia, Halladjian, D'Amours, and Frayret (2011), agents are used to distribute the problem into its participants, which collaborate to solve their local problems. Although this review applies to supply chain management, conclusions can be extended to the study case on automated laboratories, as they have to be supplied with samples and sample ordering and distribution has to be solved.

In Armendáriz *et al*. (2011), a business model on a carpooling application is created upon an ABM. In this model, passengers can share cars that move autonomously in a network with independent traffic lights and local conflict solving at intersections. This model can only be successful if users are matched to the right cars in real-time. Similarly, in automated laboratories, samples should be grouped so that each group may follow the same minimal route.

2.2 ABMs as System Controllers

Most applications require be implemented with systems able to work with dynamically changing demands, and transportation systems are not an exception. The paper by De Wolf and Holvoet (2003) follows the same reasoning and, as other authors, state that systems should be transformed into autonomic ones to cope with complexity.

In autonomic systems, components tell others what they want and not how to attain the corresponding goals. Following this principle, the automated laboratory for the study case is divided into two parts: the one of the transportation and the one for the application, which tells the first one what is needed but no how it must be fulfilled.

De Wolf and Holvoet (2003) propose using ABM to build a model of the system and include one module to analyze de dynamics of the system (in our case, this module is in charge of measuring differences between expected behaviour and sensed one) and another to control the rest of the system (in our case, the physical agents which are controlled by their virtual counterparts). Additionally, cost functions have to be measured with respect to model parameters so they can be adjusted to keep efficiency at the desired reference level. This is a top-level controller built on top of local, agent controllers. (We have not planned to include such a top-level controller because of the relative simplicity of the case study.)

The main problem to use ABM as a controller is that ABM can run in real time with the physical requirements of the system and its application.

2.3 ABM to Control Traffic in Transportation Systems

Systems of agents have already been used to control traffic. The idea is to have a traffic system that can be self-regulated from individual choices and that requires as little assistance as possible from agents at a higher level of hierarchy. In other words, the idea is that transport orders from the applications are handled by transportation agents in an autonomous manner, with minimal information from other agents, including those who may act as planners and routers.

Fig. 2 illustrates how this control scheme is organized. Topology of the plant and the number of transportation agents (here and after referred to as taxis) are among the variables that configure the model that is used for controlling the real plant.

The higher level modules of the taxis ($\{T_i\}$) get orders from agents that represent other modules of the application ($\{A_j\}$) and try to fulfil them.

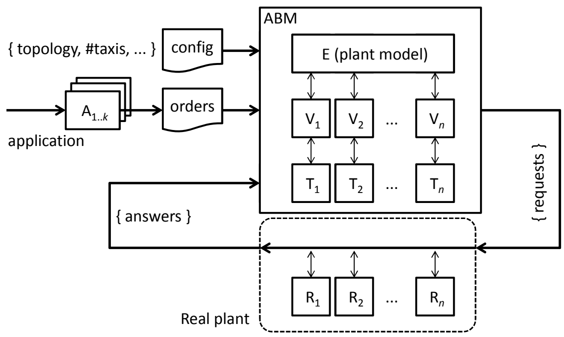

Figure 2: Architecture of an ABM controller.

To do so, taxis must negotiate with application agents $\{A_j\}$ and other workmates which jobs they take and, when in transit, how can they be done in the more efficient way. In taking the decisions, taxis have knowledge of their own state and the state of their lower-level counterparts ($\{V_i\}$). Results of deliberations are transformed into requests to the $\{V_i\}$ and also to the real robots $\{R_i\}$. The last set of requests is, in fact, the output of the ABM controller. And the inputs include the replies to these requests from robots, hence closing the loop between the controller and the controlled system.

Note that the variability of incoming orders increases the complexity of a central planner and/or a traffic coordinator thus making it difficult to attain any gain in cost or throughput. Consequently, the taxis operate autonomously, with less guarantee of optimality but with the benefits of this mode of operation with respect to flexibility and robustness.

3 AUTOMATED LABORATORIES

Laboratories of clinical analyses have progressively been transformed into complex “manufacturing” facilities, able to produce thousands of analyses per hour from blood and other body fluids’ samples.

In these facilities, samples are dropped into tubes that are placed in racks which are delivered to different analyzing machines by using a conveyor system (Ribas-Xirgo, Miró-Vicente, Chaile and Velasco-González, 2012).

Unfortunately, some tests done by analyzers have to be repeated, not all racks have to stop at the same analyzers and there can be several analyzers which can do the same job, though with different workload capacities.

As a result, the complexity of managing this kind of laboratories is quite high, even though the use of conveyors sets some layout constraints to the transport systems thus limiting it. Things can go worse when conveyors are replaced with agent-based AGVs (automated-guided vehicles), as they have more degrees of freedom.

However, the choice for autonomous AGVs relieves the plant planner from operating with lots of data and makes it possible to obtain optimal transport orders, which will be taken by AGVs. Additionally, the MAS-based transport gains flexibility and robustness.

In the following, we shall explain the details about the layout of the plant and the behavior of the AGVs for the study case selected to validate our development and deployment framework.

3.1 Plant

To include most of the characteristics of actual plants of automated laboratories, the case study includes four different analyzers: one ion-counting unit, one coagulometry analyzer and two biochemical units, as most of the samples require measuring biochemical factors.

The layout of the plant (Fig. 3) is quite similar to that of a conveyor system where conveyors are replaced by autonomous AGVs, thus not requiring much infrastructure. In this case, to simplify vehicle operations, robots move around by following a line with marks, which are used by AGVs to self-locate within the plant map. In fact, they are used to indicate a programming spot, a bifurcation or a junction. The type of the mark is determined by AGVs in accordance with their location in the plant.

The programming spots at the loading dock (bottom left) and at the beginning of the return lane (second to topmost and rightmost cross) are places where the LIMS tell AGVs which kind of tests should be done on the samples they carry and which tests have been done successfully, respectively.

There is a re-circulating lane (middle line) that can be used by AGVs that carry samples that wait for acknowledgement of their tests or to repeat them, in case the tests go wrong.

At the beginning of the returning lane (topmost rightmost mark), AGVs have their tube racks unloaded, and, at the waiting queue, they have their batteries re-charged (if needed), and follow their pace to the programming spot.

3.2 Transportation Agents

In the proposed system, samples are transported from one point to another by robots, which are intended to give the whole flexibility and fault-tolerance, and to relieve the global controller from most of the systems' complexity in planning (Himoff, Rzevski, Hinton and Skobelev, 2006).

As already indicated, the overall planning is done by the LIMSs, which link samples and tests and, subsequently, samples to sets of analyzers. These data are used by taxis to determine their goals, *i.e.* their destinations.

In Wojtusiak, Warden, and Herzog (2011) it is shown that an evolutionary learning process to optimize individual order selection and routing gives best results that a greedy approach. However, because of the simplicity of the case-study network and that there are only one collection and one ending spots, we have opted by implementing a greedy approach with some learning from experience when solving conflicts.

Each taxi features an AGV that is aware of its own position, recognizes the environment and communicates with others to coordinate their movements. AGVs use information about the plant to determine to which analyzer they should go to satisfy the requirements of their loads the fastest they can. Currently, in our model, AGVs randomly choose from compatible goals, i.e. they can go to either biochemical analyzer on a random basis, as the focus of this work is about validating the proposed ABM-based controller.

When an AGV arrives at its destination, it docks at the port of the corresponding analyzer so that it can begin with its work. In case it is busy, the taxi puts itself on hold in a parking area (short wait) or goes on to a compatible destination or to the re-circulation lane (long wait).

In the model, the high-level of taxis $\{T_i\}$ is responsible for telling the lower-levels, simulated $\{V_i\}$ and real $\{R_i\}$, what actions to do, and the low levels to reply with data about the results of these actions. Note that $\{T_i\}$ and $\{V_i\}$ are executed on an ABM simulator while $\{R_i\}$ on the embedded controllers of the robots of the system, i.e. on actual AGVs. At present, the ABM is run on Netlogo and the robots are Boebots from Parallax.

4 PLANT CHARACTERIZATION

Model accuracy depends on good characterization of the actual plant. Static data such as traffic network and nominal characteristics of vehicles such as average speed and energy consumption can be used for functional validation of the system and as a set of initial values for the model. However, in order to control a real plant, parameters should be as accurate as possible so they have to be estimated from a series of test runs.

Our model includes a mechanism for parameter identification and updating that can be used for both plant characterization and continuous model adaptation.

To activate the mechanism, the model has to be set to real-time mode instead of discrete mode. In fact, this mode of operation is the only one possible when working with actual taxis.

Plant characteristics are of two types: the ones that define its traffic network and the ones that define the functional and non-functional behaviour of the taxis. We assume the traffic network be constant and defined by a topological graph that is known to all taxis of the system.

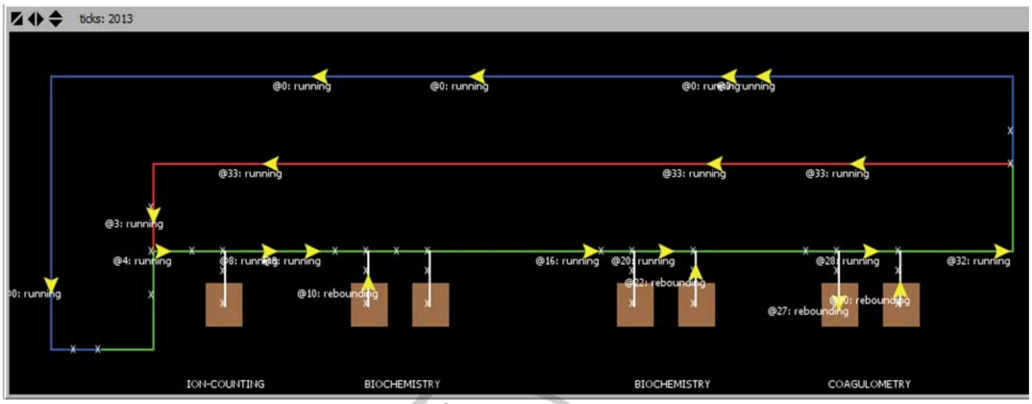

Figure 3: Plant layout from its simulator within Netlogo.

Each taxi tags the topological graph with data related to the cost it takes to itself to get to a node or to perform some action at a node.

In a simple version, the cost data consists of the time to go from a node to another and the time devoted at each node to decide which outgoing arc to take.

For instance, the characterization of an arc for a given taxi consists of measuring how long it takes to travel from the origin to the destination. And the characterization of the time required to perform an action is done by measuring the time to complete it after being requested to. Such measures are done indirectly from messages between the ABM and the physical part of the taxi.

For every order request from a T_i to a R_i, it is recorded the delay time that takes to T_i to get a reply from R_i. This delay is compared to the previous one in the same node or arc of the map graph and updated accordingly so that further decisions of T_i and the reactive behaviour of V_i are more accurate to the reality. Note that the characterization is made at every communication so taxis may end up by having very different "views" of the traffic network and behaving in a very different manner.

Other characteristics can be measured by the robots and transmitted with the acknowledgement messages but, in the first version of the proposed model, these are not taken into account.

5 MIXED-REALITY SIMULATION AND CONTROL ENVIRONMENT

To accurately monitor any timing problem between controller and real robots, and also when operating with real robots in a mixed-reality environment, messages from $\{R_i\}$ and $\{V_i\}$ have to be synchronized.

In this section we shall explain the problems of controlling real AGVs with an ABM and of synchronizing the reality and the simulation.

5.1 Real-Time Monitoring

In real-time mode, all delays are compared to the worst-case execution time (WCET) of the body of the main control loop so to guarantee that no inputs from the plant will be lost or taken into account out of time. Therefore the control loop has a cycle period only compatible with robots whose embedded controllers can understand quite complex instructions, with execution times larger than the WCET of the model.

This is the usual case in transport systems with lower-level parts of taxis executing actions such as "go to the next landmark", "take the next turning to the right" or "dock at the machine pier".

To prevent ABM from missing input data or sending outdated orders, our model controls that all measured delays go above 2 times the model WCET.

There are some alternatives to operate with delays closer to the WCET such as including time-stamps into the messages or minimizing it by appropriately modifying the scheduling of agent execution, as presented by Mathieu and Secq (2012).

However, they are not implemented because experiments show that the previous rule is normally satisfied.

For instance, a simulation of an ABM of the case study with 20 AGVs gives a WCET of 16mS. When operated with real robots, communication is estimated (we have real data only for up to 4 robots) to take an extra time of 20mS per control cycle. As a consequence, the ABM controller can handle real time at frequencies of 14 cycles per second.

This frequency implies that simulated ABM can control 20 real robots $\{R_i\}$ with an spatial resolution under the cm, which is acceptable for the laboratory previously presented, even if working at 25% more than the maximum throughput of the top current analyzers (8000 tests/hour). Note that marks and objects are more than one cm away from each other.

5.2 Synchronization with Reality

The view of the model enables creating a mixed-reality environment in which it is possible to design, supervise and control transport systems of applications.

As already explained, the model records the actual delays between requests from T_i and corresponding acknowledgements from R_i, but also compares them to the delays from V_i.

For every request-ack. pair between T_i and $\{R_i, V_i\}$, if the actual delay is longer, the view of the corresponding agent remains stand still until the time gap is covered. On the other side, if the real delay is shorter than the expected one, the view is updated for the missed, un-simulated time. This fact implies that the WCET must be twice as short as the shortest delay so that these extra periods required by the simulator to synchronize virtual robots to their physical counterparts do not cause any loss in inputs from the actual plant. Therefore this synchronizing mechanism works fine only if the control loop period is shorter than half the delays to be measured.

6 CONCLUSIONS

In this work we have focused on the internal transportation aspect of systems that run applications on the industrial domain and proposed a framework to design and deploy the corresponding subsystems.

The framework uses an ABM simulator as a key tool that is used in the following cases: 1) for functional validation; 2) for plant characterization, which includes testing whether real time requirements are met, parameter identification, and controller setup, and 3) as a model for the controller of the transportation system, including a mixed-reality environment for monitoring and supervising in human-assisted operation.

We have shown that the higher levels can be simulated and, thus, verified in a straithforward manner and that it is possible to synchronize the model execution with the real plant to use it as an actual controller.

Preliminar results show that the proposed strategy minimizes the time-to-prototype as the development platform is the same that the deployment one.

In the near future we expect to have complete experimental results on real-time control with this framework and to develop strategies to solve synchronization conflicts when simulation and reality differ.

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