Multilevel Modelling of Urban Transport Infrastructure

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Abstract: This article covers the transportation processes modeling in the Intelligent Transportation System environment. The combined microscopic and mesoscopic simulation is included. This article is dedicated to solving the problem of data preservation during the transition from a microscopic to a mesoscopic model. The solution suggests modifying the multi-agent transportation system, and using artificial neural networks, considering implementation of the unique architecture of an intelligent agent which collects additional information to be forwarded to the next simulation level. The article describes the microsimulation process implementation in the multi-agent system MATSim. A Ward neural network (trained using the data transferred from the microscopic level) is used for the processing for the mesoscopic level.

1 INTRODUCTION

The problem of optimizing transport processes in the city is one of the most important in the Intelligent Transportation Systems. The most acute problems are traffic accidents and traffic congestion on the street and road network (SRN) (Shahin, 2012). The solution of these problems and their consequences requires a comprehensive analysis of transport infrastructure. The most robust investigation method of the transport infrastructure is modeling (Gregoriades, 2012).

Conventionally, three levels of simulated objects are considered: microscopic, mesoscopic and macroscopic levels. At the microscopic level separate vehicles and technical means of traffic management are considered (Cavar, 2013). On the mesoscopic level homogeneous groups of vehicles are considered, which have common characteristics as density, intensity and speed (Savrasovs, 2014). The macroscopic level of transport flows of the entire city is described by using the differential equations system (Burghout, 2004). Microscopic and mesoscopic models can also be used to describe the traffic system of the entire city, however, these approaches may result in performance issues (Kolosz, 2014).

The specifics of each level can be combined into a single software system to improve its overall efficiency. Existing software systems implement such integration by calculating the macroscopic characteristics by referencing the microscopic data (Gaud, 2008). This approach results in losing a large amount of valuable information related to the hidden patterns in the microscopic model. The data loss applies to behavioral and communicative features of individual agents, which should be reflected in the dynamic characteristics of the averaged homogeneous groups. Moreover, transitioning to a higher level of modeling results in a loss of feedback between agents and the environment, this introduces inaccuracies in the calculation of the parameters of transport infrastructure (Kumar, 2014). Calculation of tension at gravity points, which depends on observables provided by individual agents, can serve as an example.

Locating and keeping the hidden patterns in models of higher order is a difficult task, because it requires the development of methods which operate at the junction of traffic flows theory, multi-agent systems and artificial intelligence systems. The article provides a unique architecture of the microscopic traffic simulator which allows the transfer of data to the mesoscopic level with minimal loss of information.

2 INTELLIGENT AGENT

Intelligent agents $A^I=\{a^I_1,\dots,a^I_N\}$ are used in modeling of the traffic flows object (Russell, 2010). This section is devoted to the description of the architecture and the behavior of intelligent agents in the road network model.

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Refer to figure 1 to see the architecture of the intelligent agent from the set A^I. The designed architecture allows agents to interact with each other and with the environment, which changes are not predefined.

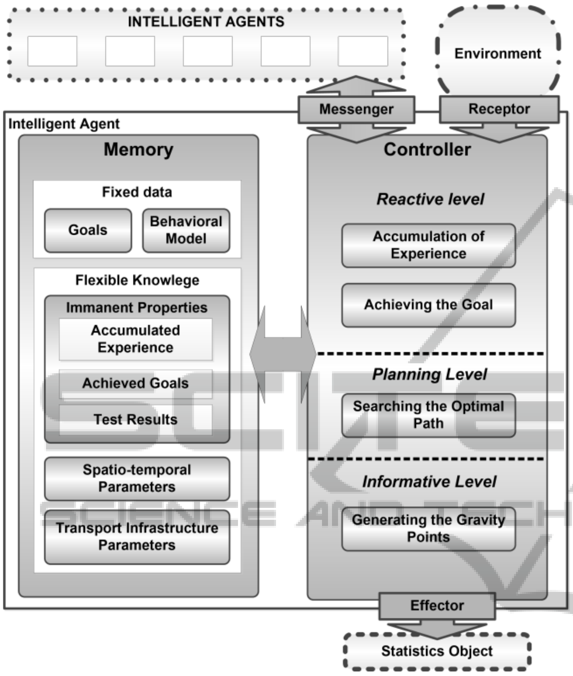

Figure 1: Intelligent agent architecture.

The architecture of an intelligent agent is represented by the following structural units: a controller, a memory, the means of communication with the environment (receptor, messenger and effector), and the means of interaction between these blocks.

The receptor receives information from the environment, and determines further action on its processing and stores the required data in the memory.

The effector collects information about the gravity points P^A (Mikheeva, 2014) during the modeling object process. The collected information is used by the statistics gathering object. At the end of each reporting period Δt, which corresponds to a calendar day, the agent a^I_i generates a report, which represents a dataset containing the following data:

- p^{opt}_i - the selected optimal path;
- t^{opt} - the time spent to complete the optimal path p^{opt}_i;
- p^A_i - the list of gravity points with the values of their load u^A_i.

The messenger is designed for communication between intelligent agents and provides composing, sending, and receiving messages.

The memory unit is used to store the collected data. There are two memory blocks: area of the fixed data (obtained at initialization), and the area of the flexible knowledge (data changed during processing by the agent).

The controller provides data processing, generates reactions according to the data received from receptors and messengers, solves problems, and generates data for the effector. The agent's controller is divided into three planning levels: reactive and informative.

At the planning level agents a^I_i are initialized according to one of the driver models M^{beh} (Gonzalez, 2008). Determination of the scope occurs according to the selected model $m^{beh}(a^I_i) \in M^{beh}$, which depends on the SRN model, and the results of calculation of the optimal route by the SRN graph $G'=(V',E')$ according to the assigned chain of correspondences.

The problem of navigating through the SRN graph G' is solved by considering the individual driver behavior model $m^{beh}(a^I_i)$ at the reactive level. The task of processing the signals from the receptor and the messenger is also resolved at this level. The reactive subsystem is based on neural network technology, which matches typical situations in the environment with the reaction of agents' behavior. This approach allows making effective decisions while the intelligent agents move along the street and road network graph.

The informative level is a neural network training process. The neural network accumulates knowledge about dislocation and load values in the gravity points P^A.

The proposed architecture of an intelligent agent provides necessary qualities of its behavior, such as complexity, autonomy and intelligence. It is achieved by using a neural network in an intelligent agent adapted to working in a transport infrastructure modeling environment.

3 MICROSCOPIC TRANSPORT SIMULATOR

3.1 Simulator Mathematical Model

Data generated by the simulation of a traffic flow includes amount, dislocation, and load values of gravity points of a city. The modeling object A^M is used for traffic simulation, which generates the following objects: the coordination object, the statistics object, and the set of intelligent agents $A^I=\{a^I_1,\ldots,a^I_N\}$. The listed objects are represented in the common environment E and interact with each other.

The coordination object is used for the management of intelligent agents $A^I=\{a^I_1,\ldots,a^I_N\}$. The coordination object determines the creation time and the time of achieving the set goals for each agent a^I_i,. The coordination object performs the accounting of time in the following format: "season", "day of month", "weekday", "hour" (Kravets, 2013).

The statistics object is used to predict the tension on the parts of the SRN.

The mathematical model of the modeling object A^M is as follows:

$$A^M = \{E, A^I, S^E_{out}, M^P, F^A\} \quad (1)$$

where E - is a finite set of objects in the environment, including the SRN model objects and transport infrastructure;

$A^I=\{a^I_1,\ldots,a^I_N\}$ is the finite set of intelligent agents, that are represented by an extended mathematical model;

S^E_{out} – the set of states of the environment E;

M^P – a set of traffic laws;

F^A – a set of functions describing the changes in the state of transport infrastructure (Saprykina, 2013).

3.2 Simulator Implementation

Analysis of the street and road network configuration is performed by the use of simulation tools based on freeware component library MATSim (Multi-Agent Transport Simulation) (Rieser, 2014). Modeling objects designed in the previous sections are created in the MATSim environment by extending the built-in classes. For example, a MATSim agent class is extended to the developed intelligent agent. Intelligent agents act as mini-systems involved in continuous interaction with each other, and are capable of independent actions. Agents are coordinated and their actions are structured according to the current objectives.

The system contains the following functional blocks:

- micro-modeling simulation of the transport flow;
- collection and processing of the simulation process data;
- dynamic visualization of the simulated process.

A city map is converted from OpenStreetMap format to the MATSim internal format. The model of a map is a sequence of road sectors, each containing the following immanent properties: capacity; maximum allowed speed of movement; number of lanes in the SRN area; direction of movement; road surface quality.

The MATSim core calculates routes of agents' movement at a given time, with all the street and road network attributes. While moving about the map agents update their state and collect traffic congestion and tension data storing it in a database. During the simulation in the output folder files are created with the results that contain the full path and travel time of each agent.

The simulation result can be reviewed by uploading files obtained in the previous step into a dynamic visualization unit (Fig. 2). The subsystem allows seeing the distribution of agents over time, tracking problematic time intervals and areas of the city and figuring out gravity points.

Figure 2: Visualising the process of microsimulation.

Agents are having speed, which close to the free speed route, are highlighted in green while modeling the transport process. The red color indicates traffic congestions. Figure 2 shows traffic congestions on major highways of the Samara city at the evening rush hour. The simulation results match the actual situation on the street and road network of the city, as confirmed by field studies and the data of traffic information web services.

4 TRANSITION TO MESOSCOPIC LEVEL

Tension, density, and intensity in certain SRN areas are represented at the mesoscopic level of the city transport model (Kerner, 2009). Let us review the construction of the tension function of the gravity points using the data obtained at the microscopic level. The statistics gathering object uses a neural network. Training of the neural network is performed during the intelligent agents' a^I_i moving on the SRN graph G' according to the set of rules (intelligent function). Each intelligent agent a^I_i dynamically trains the neural network throughout its life cycle. A trained neural network is able to predict tension values at any given gravity point.

The neural network used in the statistics object is a three-layered Ward neural network, which is capable of conducting a qualitative analysis by allocating the initial data in various aspects. This is achieved by a special type of neural network architecture, a hidden layer which is divided into several blocks. In this case each block has its own transfer function that facilitates the parallel processing of signals received from the input layer. Architecture of the Ward neural network is shown in Figure 3. The input layer of the neural network consists of the following parameters: (x^A, y^A) - coordinates of a gravity point, (x^0, y^0), (x^N, y^N) - coordinates of the beginning and the end of the arc of the graph corresponding to the SRN section, l_i - length of the SRN section, n^α_i - number of lanes on an SRN section in the forward direction, n^β_i - number of lanes on SRN section in the opposite direction, α - rotation angle of the forward direction, β - rotation angle of the opposite direction, τ – temporal parameters.

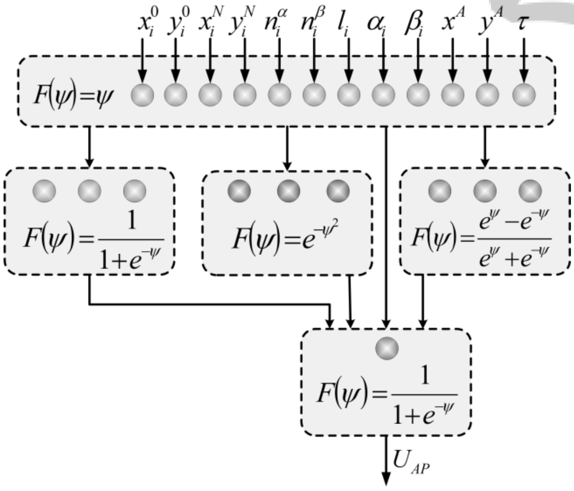

Figure 3: Architecture of the Ward neural network.

A linear activation function $F(\psi)=\psi$ is used for the input layer of the Ward neural network. The number of neurons in the input layer is dictated by the number of variables. The hidden layer is represented by the three blocks. Activation functions for the hidden layer units are chosen experimentally, which are:

- sigmoid:

$$F(\psi)=\frac{1}{1+e^{-\psi}} \tag{2}$$

- hyperbolic tangent:

$$F(\psi)=\frac{e^{\psi}-e^{-\psi}}{e^{\psi}+e^{-\psi}} \tag{3}$$

- radial basis:

$$F(\psi)=e^{-\psi^2} \tag{4}$$

A sigmoid activation function is used at the output layer. The number of neurons in the hidden layer is calculated as follows:

$$N^{\text{hidden}}=\left[\frac{N^{in}+N^{out}}{2}+\sqrt{N^{\exp}}\right] \tag{5}$$

where:

N^{in} -is the number of neurons in the input layer (N^{in}=11);

N^{out} - is the number of neurons in the output layer (N^{out} =1);

N^{exp} - is the number of the performed experiments (Rutkovskaya, 2004).

Ward neural network training is performed by backpropagation. Selection of weighs occurs every time when applying tension information $u^A_i \in U$ at the gravity point p^A_i obtained from the agent $a^I_i \in A^I$ while transferring the data to the neural network.

Thus, the statistics object shows the dependence of the temporal and spatial characteristics of the investigated area on the tension $u^A_i \in U$ of gravity points $p^A_i \in P^A$. The resulting neural network is capable of storing the data obtained at the microscopic level and solving transportation problems on mesoscopic and macroscopic levels.

5 CONCLUSIONS AND FUTURE WORK

This article describes the modified microscopic traffic simulator with agents figuring out knowledge about SRN bottlenecks to transfer to a higher modeling level. This information is used at the mesoscopic level to train the neural network, which allows keeping hidden patterns in the form of synaptic connections. The discovered dependencies allow analyzing the modified transport infrastructure without running additional simulation cycles.

The work on constructing models of transition from mesoscopic to macroscopic parameters allowing finding the optimal structure of street and road network is underway.

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