Traffic-related Knowledge Acquired by Interaction with Experts*

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Abstract. We present our research on acquiring domain knowledge related to urban vehicular traffic by means of interaction with experts. Such knowledge is needed in knowledge discovery and data mining for approximation of complex vague concepts from the road traffic. According to perception based computing paradigm, this can be done by construction of hierarchical classifiers supported with expert knowledge. We treat traffic, especially urban traffic, as a complex process having hierarchical structure. Complexity of this process makes traffic data massive and complex, what makes domain oriented hierarchical classifiers indispensable here. We propose a method of traffic domain knowledge acquisition by interaction with experts aimed at construction of such classifiers.

Keywords: vehicular traffic, interaction with experts, vague concepts, knowledge discovery, perception based computing, hierarchical classifiers.

1 Introduction

Vehicular traffic is a vital phenomenon for the contemporary city. It has a significant impact on environment and life of many people. Understanding the phenomenon and learning how to manage it are crucial tasks for functioning and development of the contemporary city. One of the main issues here is to learn from data knowledge about urban traffic as a complex process. It involves learning detection of traffic jams and recognition of traffic congestion levels. In order to learn such knowledge we have to learn basic traffic concepts such as e.g. *traffic jam*, *traffic congestion*, *traffic jam formation*. But here we face two challenges. These concepts are complex vague concepts, thus they are hardly mathematically defined. Instead of that we can learn them from experts, i.e. acquiring from experts the relevant concepts and approximating them by urban traffic data, i.e. lower level data which describe urban traffic. Thus some form

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of interaction with experts is needed. Elaborating an interaction method is the first challenge faced in this paper. Urban traffic data are good example of Big Data, they are massive and qualitatively complex what makes their processing computationally expensive. They become even more computationally expensive in the task of adaptive, autonomous, on-line control which is one of the main tasks in traffic research. This traffic control task gives the second challenge. We do not face this challenge directly in our paper. We discuss it in the light of perception based computing paradigm [33, 34] pointing out a possible solution: construction of hierarchical classifiers supported by domain knowledge [3].

In this research, we focus on a single basic traffic concept - *traffic congestion on a single crossroad* - and we elaborate methods for approximating this concept from sensory data. Our sensory data come from simulating traffic using the Traffic Simulation Framework (TSF) software [10–12]. Data from the software may slightly differ from real-world traffic data (which are very difficult to obtain), but are confirmed to be quite realistic [13], enough to conduct our research.

The paper has the following organization. Section 2 describes past approaches to traffic modeling, recent approaches based on probabilistic cellular automata and the model developed by P. Gora [10, 12] which was implemented in TSF software and is used in our research. Section 3 outlines our approach for acquisition of traffic knowledge, motivates why we chose such approach and explains how such knowledge may be applied to approximating complex, high-level traffic concepts from sensory data, according to the perception based computing paradigm. Section 4 presents the design of our experiment, the procedure of dialogizing with domain experts and values of simulation parameters used in our experiment. Section 5 describes the evaluation of data obtained in the experiment and conclusions that we drawn based on analyzing acquired data and feedback from experts. Section 6 concludes the paper.

2 Modeling urban vehicular traffic

Despite many years of extensive research, it is still difficult and challenging task to model the urban traffic with satisfactory accuracy, either using standard mathematical tools or computer simulations. The proper model should take into account many factors, such as: modeling drivers behavior, Origin-Destination matrix, location and configuration of traffic signals, the weather, road works etc. The situation is much simpler in case of a traffic on highways, where the traffic is only in one or two directions, there are no traffic lights, the number of possible interactions between cars is relatively small.

There are three major classes of traffic models: macroscopic, microscopic and mesoscopic. Macroscopic traffic models treat all cars aggregately and describe relationships between traffic congestion, traffic density and average speed. Such models are usually based on analogy to other, well-known physical phenomena, such as fluid dynamics [19, 18] or kinetic gas theory [27]. Some models were able to reproduce properties of traffic on highways, e.g. the pioneering macroscopic model, Lighthill-Whitham model [19], is able to reproduce *shockwaves*. Some macroscopic models have been already applied in commercial products, such as PTV VISUM [40], and are applied to planning public transport, construction and development of roads, analyzing economic efficiencies of transport solutions, modeling travel demand etc.

The next class of models are microscopic models which model drive of every single car. For instance, the Nagel-Schreckenberg model (Na-Sch model) is based on a probabilistic cellular automaton and is able to explain and reproduce spontaneous traffic jam formation on highways [21, 32]. Space, time and speeds are discrete in this model, the road is divided into cells, which may be empty or occupied by at least one car. Transition rules, determining driver's behavior, are defined by properly selected rules. The most fascinating thing about the model is that it is based on a very simple, natural transition rules, and is able to reproduce traffic on highways with very good accuracy [21]. The model was broadly investigated and generalized, e.g. to simulate 2-lane traffic [29] or simple crossroads [7]. Also, generalizations of the model were applied in real-world traffic simulations systems, e.g. in the system Autobahn [2], which simulates and predicts the traffic in Germany, and in the software Traffic Simulation Framework (TSF), [10, 12], which we use in our research. Recently, there are developed much more advanced microscopic models which take into account drivers behavior (e.g. Intelligent Driver Model [36]).

There are also mesoscopic models which propagates "packets" of cars. Such models also give good results in case of modeling large-scale urban traffic [5].

2.1 Traffic Simulation Framework model

The Na-Sch model was used by P. Gora to develop a new traffic simulation model, the TSF model [10, 12]. The model extends the standard Na-Sch model and allows conducting simulations on a realistic road network, represented as a directed graph. Cars drive through the road network on edges, which consist of tapes (representing road lanes), divided into cells, as in the original model. Some vertices contain traffic lights, which are objects characterized by location, duration of a red phase, duration of a green phase and offset.

The model takes into account many factors, e.g. driver's profile, road's profile, location and configuration of traffic signals, distributions of start and destination points. Currently driver's profile specifies aggressiveness of driver, which determines the maximal car's speed on a given road, but the profile could be easily extended in the future (in fact, there already exist microscopic models which include much more details with respect to driver's behavior, e.g. Intelligent Driver Model [36]). Road's profile determines number of lanes and normal distribution of maximal speed of drivers, which, together with a driver's profile, determines the maximal speed of a car on a given road [10, 12]. Distributions of start and destination points are defined on graph vertices and specify how to choose these points for driver's route (distributions may be replaced by the Origin-Destination matrix, if this is available). After specifying distributions of start and destination points routes are calculated using the A* algorithm [6].

The move of every car is specified by transition rules of a cellular automaton being an extension of the standard Nagel-Schreckenberg model [21, 32, 10, 12].

2.2 Traffic Simulator Framework implementation

The TSF model was implemented in Traffic Simulation Framework, advanced software for simulating and investigating vehicular traffic in cities. TSF is being developed in C# and runs using .NET Framework platform, it employs maps from the OpenStreetMap project [22] and real traffic data for Warsaw from Municipal Administration of Urban Roads in Warsaw [42]. Currently TSF is able to simulate realistic traffic in Warsaw with more than 10^5 cars faster than real-time[1] and it was confirmed by Warsaw citizens that the software can reproduce traffic jams in the same places as they occur in reality. TSF possesses a multi-functional Graphical User Interface (GUI) and allows modifying map parameters and simulation parameters from the GUI level. Currently it is possible to edit locations and configurations of traffic signals, distributions of start and destination points, parameters of different types of road network segments (e.g. parameters specifying normal distributions of the maximal speed on a given road segment). Also, it is possible to generate large number of routes for cars, according to given distributions of starting points and destination points.

TSF is still being developed, its functionality was described in details in papers [10, 12]. The software has been already used for generating data for the IEEE ICDM 2010 contest on traffic prediction [13, 37]. The contest was sponsored by TomTom, held under the patronage of IEEE, ICDM conference and the President of Warsaw, Mrs. Hanna Gronkiewicz-Waltz. It was an important data mining event, which attracted 575 participating teams, which submitted in total almost 5000 solutions. Many of those solutions are interesting data mining algorithms for predicting traffic congestion, average speeds and traffic jams occurrences. The best solutions were published in proceeding from the ICDM 2010 conference [9], some of them are also elaborated in the TunedIT blog [38]. Data for the contest was released for the public use to enable post-challenge research, resulting in few more interesting algorithms [30, 43].

Currently TSF is also used for designing evolutionary algorithms (e.g. genetic algorithms [11]) for optimizing traffic by configuring traffic lights. It is also used by scientists from many countries in their research on traffic modeling, analysis and prediction, e.g. [28, 30, 43]. The recent application of the software is acquisition of traffic-related domain knowledge by interaction with experts, which is a topic of the paper and is described in details in next sections.

3 Traffic knowledge acquisition - Perception Based Computing approach

This research is aimed at acquisition of traffic domain knowledge by interaction with experts. Traffic is a very complex phenomenon and many high level

[1] Simulations run on ThinkPad T400, Intel Core 2 Duo T9600, 2.8 GHz, 4 GB RAM

concepts related to that phenomenon are complex and vague (e.g. *large traffic congestion* or *formation of a traffic jam*). These concepts are hardly mathematically defined and may also depend on many factors such as city, type of a crossroad etc. In some cases there are engineering approaches which try to define such concepts precisely (e.g. *levels of service* aim to approximate traffic congestion levels [15]), but in fact these are just approximations and many spatio-temporal concepts related to urban traffic dynamics are beyond the scope of precise, mathematical definitions, because of their vagueness. However, human brain can recognize such concepts much better than machines. Drivers and pedestrians participating in urban traffic are able to recognize the traffic situation quickly and effortlessly and can easily decide whether in a given traffic situation there is a traffic jam or not. It should be highlighted that in most cases, drivers and pedestrians are not transportation science experts or traffic engineers. Contrary, they can be viewed as *experts - practitioners*. They are *practitioners* because they are traffic agents, taking part and interacting each other in urban traffic. The way in which they make their decisions or results of those decisions influence urban traffic as a complex hierarchically structured process. One of the main principles in perception based computing states that perception is action oriented. In the case of algorithm evaluation it means that algorithms should be tested on the basis of efficiency of actions that are managed or controlled by those algorithms.

The long-term goal of our research is an optimization of traffic control. Knowledge collected from experts during this research will be used for construction of classifiers evaluating traffic congestion and, among others, recognizing appearance of traffic jams. And finally these classifiers can be used for evaluation of traffic control optimization algorithms as one of the possible ways, in addition to delay measuring. Therefore, the choice of drivers and pedestrians as experts transferring knowledge about traffic is not arbitrary since they are agents interacting in the urban traffic and both, they and their knowledge, are elements of the urban traffic complex system.

According to PBC approach, for concept learning hierarchical classifiers will be used. Hierarchical classifiers, as other classifiers, are decision algorithms that map objects to decisions [1, 4], but they are doing that in a hierarchical way. Objects could be described by low-level numerical or symbolical attributes. Decisions, in many cases, are vague, complex concepts, which are semantically distant from original low-level data. Hierarchical classifiers could be viewed as tools that may be used to cover that distance by approximating complex, vague concepts, using low-level data. In such classifiers the classification process goes from input data to decisions through at least few hierarchy levels, from lower data levels to higher, more abstract, complex concepts levels. Objects and/or attributes on higher levels are constructed based on objects and/or attributes from lower levels [33, 34]. This process may be supported by domain knowledge, given e.g. in the form of ontologies. To cover the semantic distance, training sets can be constructed with experts support. Decisions could be also complex, temporal or spatio-temporal objects as automated planning of complex objects behavior, e.g. safe driving through a crossroad or medical diagnosis, see [3].

As we mention above, in this research, expert knowledge is collected for construction of classifiers approximating the traffic congestion concepts by means of low-level traffic data. Low-level data, such as number of cars, car's position, current car's speed, are taken from TSF traffic simulator created by P. Gora [10, 12]. Data collected from simulations generally can be treated as results of measurements returned by logical sensors (see [41]). In the case of hierarchical classifiers approximating traffic concepts, such data create the first, sensory level of hierarchical approximation. Objects and attributes from consecutive hierarchy levels can be constructed on the basis of objects and attributes from lower levels of hierarchy by means of information systems, decision tables and decision rules taken from the rough set theory [23–25] as it was done in [3].

4 Experiment

In perception based computing one of the main factors in hierarchical information processing is a way of granule setting or construction at every level of the hierarchy, starting from basic granules. In our research, as a basic granule in hierarchical organization of urban vehicular traffic we picked up a single crossroad. Thus the main aim of this research is to learn conceptual levels of traffic congestion and a concept of a traffic jam on a single crossroad by means of a dialog with experts.

First we prepared 51 traffic simulations corresponding to different traffic situations close to the crossroad of streets "Banacha", "Grójecka", "Bitwy Warszawskiej 1920 r." using the Traffic Simulation Framework. The area under investigation is presented in the Figure 1, it is a place where large traffic congestion occurs very often. Then we selected values of all important simulation parameters based on our past research and experiments, see Table 1.

Table 1. Simulation parameters used in our experiments

Name of the parameter	**Description**	**Value**
NrOfCars	Initial number of cars for a single traffic situation	100, 1000
Step	Duration of a single simulation step	1000 ms
TimeGap	Time after which new cars start their ride	1 step
NewCars	Number of cars starting ride after every TimeGap steps	5, 3, 1
Steps	Duration of a single simulation	600 steps
Acceleration	Acceleration of cars per simulation step	10 km/h
CrossroadPenalty	Percentage of speed reduction before the crossroad	25%
TurningPenalty	Percentage of speed reduction during turning	50%

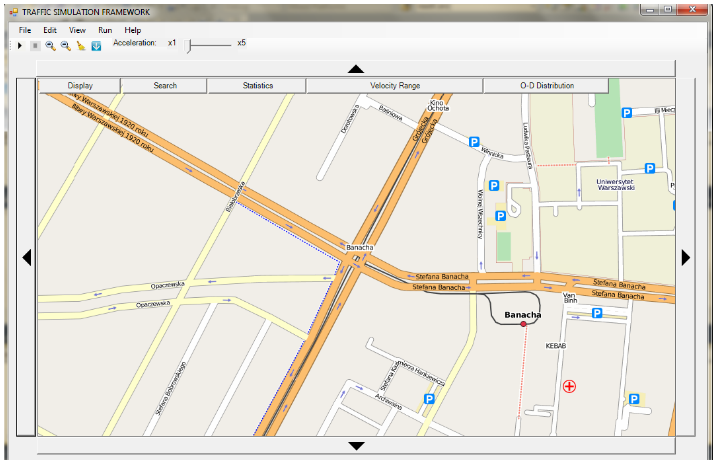

Fig. 1. Crossroad of streets Banacha, Grójecka, Bitwy Warszawskiej 1920 r. presented using TSF software.

Every simulation lasted 10 minutes, values of some parameters were common for all situations, but situations differed in the following parameters:

1. initial number of cars,
2. number of new cars that start drive in each simulation step,
3. start and destination points distributions.

We prepared 5 different distributions of starting points and 5 different distributions of destination points. Distributions of starting points were named "From East", "From West", "From North", "From South", "Uniform", distributions of destination points were named "To East", "To West", "To North", "To South", "Uniform". It gives us 25 configurations of pairs: (start points distribution, destination points distribution). Names of distributions indicates where is the major concentration of start or destination points, respectively. The detailed description of these distributions and procedures for editing start points and destination points is described in the paper [10].

For every combination of pairs (start points distribution, destination points distribution) we still have few degrees of freedom that can be manipulated in order to produce different simulation scenarios. Some of these degrees of freedom correspond to parameters named in the first column of the table 1: $NrOfCars$, $NewCars$, $Acceleration$, $CrossroadPenalty$, $TurningPenalty$. Other parameters may be related to the initial configuration of traffic signals at the crossroad or maximal speed permissible on a given street. For our current research we needed only 51 simulation scenarios, so we decided to manipulate parameters $NrOfCars$ and $NewCars$. 5 different start points distributions, 5 different destination points distributions and 3 different values of the $NewCars$ parameter gives us $5 \times 5 \times 3 = 125$ possible simulation scenarios, from which we chose 48, assuming that $NrOfCars = 100$. In addition, for $NrOfCars = 1000$ we chose

$Uniform$ distribution of start points and destination points and generated 3 more situations with 3 different values of $NewCars$. It gives in total 51 traffic situations that were later simulated using the TSF software.

Every simulation was "recorded" - Traffic Simulation Framework logged information about positions and speeds of cars during the simulation and presented the same traffic situation to experts using Graphical User Interface of our software. The following information was logged out to the output file:

- Timestamp (simulation step),
- Car positions (link in the road network, position within the link, geographical longitude and latitude),
- Current car's speed (in km/h).

Such information enabled reconstruction of the situation. We assumed that duration of a single cycle of traffic lights is constant and lasts 2 minutes for every traffic signal, so every 10-minutes long situation consisted of 5 parts, each of which lasted 2 minutes and corresponded to one cycle of traffic lights. Thus we divided logs from our 10-minutes long simulations into 5 such parts (each lasted 2 minutes), to which we refer simply as *traffic cases*. Totally, it gave us 255 traffic cases.

Each of 51 situations was evaluated by domain experts and their task was to provide information about a traffic state in the area close to the crossroad. In our case (vehicular traffic in cities) a domain expert may be any person who has experience with the city traffic, the most preferable should be drivers, which use road networks in Warsaw often and have to cope with traffic jams. 1 of 51 situations was analyzed by all experts, while every situation from the rest 50 was analyzed by 3 experts, which gives 50×3 situation evaluations. Every expert analyzed 3 situations: 1 common to all experts and 2 taken from the rest 50. Therefore, we constructed $150 / 2 = 75$ different tests, one for each expert, so we needed 75 experts. In every test each 10-minutes long situation was divided into 5 traffic cases, so it was possible to show to domain experts 2-minutes long traffic cases separately. Thus, every test consisted of 15 traffic cases. Additionally, for each expert 2 traffic cases from every situation were randomly selected to be presented and labeled by an expert twice, to check consistency of experts (they were not informed that some traffic cases are repeated in a test). Therefore, every test consisted of 21 traffic cases, which were presented to the expert in a random order as a short movie in the TSF's GUI.

After presentation of a particular movie, TSF displayed the question: *What was the traffic congestion?*. Experts answered the question with one of five possible answers: *Small*, *Medium*, *Large*, *Traffic jam*, *I don't know*. The answer was given by experts using the window presented in the Figure 2. If the experts selected *I don't know* response in the first window, the system asked for selecting the closest options by displaying the window presented in the Figure 3. In the next step, the system asked experts for the response justification, which they provided in natural language using the text window with no limited number of signs. After selecting the proper answer and submitting justification, the next movie was presented to the expert.

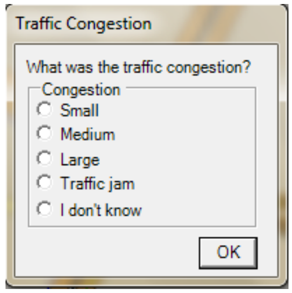

Fig. 2. Window shown to experts after every movie

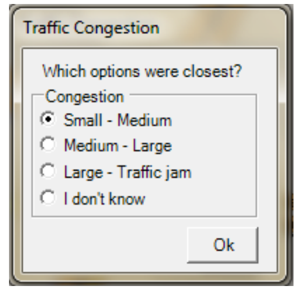

Fig. 3. Window for submitting two closest options

5 Evaluation of decisions and properties extraction

Evaluation of expert decisions can be either *expert-oriented* or *case-oriented*. In the expert-oriented evaluation we check a consistency of decisions made by a given expert. In this case, the evaluated situation should be labeled by an expert (before evaluation) at least twice for checking stability of the expert's decision making. In order to do that, from every situation two phases were selected to be labeled by an expert twice. In the case-oriented evaluation we will analyze how a given case (phase or situation) is labeled by different experts. For this purpose, every phase was labeled by three different experts. Their decisions will be used either to determine the final aggregated decision, e.g. by voting, or to find a uniformity of decisions about a given phase. It should be noted that our approach is only one of possible approaches and that decision evaluation itself is a novel and interesting issue and a topic for further research.

After providing traffic congestion answer experts were asked to justify their choice in natural language, e.g. one of experts answered that the congestion was "Small-Medium" and gave explanation: "Small traffic, but later density on the main crossroad increased".

We analyzed all such answers from experts in order to acquire important properties that were used by experts to justify their answers. Those information are our domain knowledge, which may be used to construct the ontology of traffic concepts and hierarchy of classifiers approximating such concepts, according to the perception based computing paradigm. Table 2 presents all acquired properties and their values. It is worth to emphasize that among properties we also consider "street" (as a spatial property) and "time" (as a temporal property).

We analyzed collected data and obtained decisions regarding traffic congestion obtained from the experiment for each traffic situation. We also extracted properties used by experts to explain their choice and analyzed feedback from experts. From experiment we got the following conclusions:

- There was too many test cases for one expert and the time of the experiment was too long for experts.

Table 2. Acquired traffic properties and their values

Property	**Values**
Number of cars	Small, Average, Large
Time of waiting on crossroad	Short, Medium, Long, Max 1 phase, More than 1 phase
Length of a queue on crossroad	Short, Medium, Long
Average speed of cars	High, Average, Low
Jamming	No jams, Small jam, Medium jam, Large jam
Jam dynamics	Jam onset, Jam unload
Clusters	Large clusters, Small clusters, No clusters
Street	Banacha, Bitwy Warszawskiej 1920 r., Grójecka
Time	Beginning, End, All the time

– More experts should be assigned to each situation (for now we had 3 experts for 250 situations, only 5 cases were evaluated by all 75 experts).
– It would be better if experts were informed about the progress of the experiment by displaying information “Situation nr k (from n)” before or after every test case.

6 Conclusions and future work

In the paper we propose an interactive method for acquisition of vehicular traffic domain knowledge by dialog with experts. The direct aim of our research is to prepare training urban data set for classifiers. Training urban traffic data set is needed for construction of hierarchical classifiers based on rough set methods [3, 23, 31] for approximating the concept of a traffic jam on a single crossroad. Hierarchical classifiers approximating traffic concepts can be used to construct methods for intelligent, adaptive urban traffic control as well as to evaluate them. Therefore construction of traffic hierarchical classifiers and designing intelligent, adaptive control algorithms for urban traffic are long-term goals of our research. Analyzing results of the conducted experiment, we decided to design the second experiment in order to acquire better structured data asking experts to describe every simulated situation according to properties constructed in this research and presented in Table 2. In the further steps these properties can be used as intermediating level in the construction of hierarchical classifiers. Our method will be evaluated firstly by evaluation of hierarchical classifiers induced on the basis of training sets constructed using our method. According to perception based computing paradigm our method will be also evaluated in the process of traffic optimization: optimization algorithms constructed using our classifiers will be compared to other optimization algorithms which are not supported by expert knowledge.

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