Recognizing Spatio-Temporal Traffic Patterns at Intersections Using Self-Organizing Maps

Richard Brunauer
Salzburg Research
Jakob-Haringer-Str. 5
Salzburg, 5020, Austria

richard.brunauer@salzburgresearch.at

Nina Schmitzberger
Salzburg Research
Jakob-Haringer-Str. 5
Salzburg, 5020, Austria

nina.schmitzberger@salzburgresearch.at

Karl Rehrl
Salzburg Research
Jakob-Haringer-Str. 5
Salzburg, 5020, Austria

karl.rehrl@salzburgresearch.at

ABSTRACT

Recognition and interpretation of regularly (e.g. every weekday) and irregularly (e.g. arbitrary events such as accidents) appearing traffic patterns in a road network are considered one of the most crucial questions in mobility data analysis. Knowledge of regular and irregular traffic patterns is a requirement for reliable traffic prediction or traffic control. In this paper, we present a spatio-temporal unsupervised machine learning approach using self-organizing maps (SOMs) for detecting regular traffic patterns at arbitrary intersections in a nation-wide road network. The approach applies SOMs to traffic states expressed as gradual level-of-service (LOS) values, which were derived from travel time measurements of probe vehicles. For the identification of regular patterns, they were temporally categorized by daytime (60 minutes slots) and the day of the week. The approach consists of two steps: First, an unsupervised learning approach clusters intersections with similar time-dependent gradual LOS values in order to identify similar traffic patterns. Second, a subsequent temporal analysis enables the interpretation of temporal regularities of the patterns. Based on a one-year probe vehicle dataset, we showed that the clustering reveals plausible regularities for different intersections such as interchanges, urban intersections or roundabouts that are still interpretable by humans. Furthermore, the approach can be easily adapted to identify patterns in other parts of a road network.

CCS CONCEPTS

• **Computing methodologies** → Cluster analysis • **Human-centered computing** → Heat maps • **Information systems** → Spatial-temporal systems

KEYWORDS

Spatio-temporal traffic patterns, self-organizing map, clustering, pattern recognition, probe vehicle data, floating car data

ACM Reference format:

Richard Brunauer, Nina Schmitzberger and Karl Rehrl. 2018. Recognizing Spatio – Temporal Traffic Patterns at Intersections Using Self-Organizing Maps. In *Proceedings of ACM Sigspatial conference (SIGSPATIAL '18). IWCTS, November 6, 2018, Seattle, WA, USA, 10 pages.* <https://doi.org/10.1145/3283207.3283209>

1 INTRODUCTION

The identification of regular and irregular traffic patterns in a road network is an outstanding example of a challenging spatio-temporal analysis task. The knowledge of the occurrence of regularly and irregularly appearing traffic patterns is crucial for the selection of proper strategies for traffic control, traffic prediction and transportation planning.

On the one hand, the challenge of various different road types, road constructions or intersections has to be faced. For example, an intersection is a spot in a road network where two or more roads meet. They appear as at-grade constructions, roundabouts or interchanges with grade separation (cf. Fig. 2). Such different spatial road layouts typically induce different traffic flows and states too, i.e. traffic flows on motorways significantly differ from traffic flows on urban arterials or interurban roads. Finding a unique numerical measure to describe traffic states in a holistic manner is not that obvious. Moreover, the digital representation of road networks, the road network graph, causes challenges. Spatial concepts of real world entities, such as roads or intersections, typically do not have a single digital 1-to-1 representation in data. The digital representation of an intersection may be arbitrarily cut into a set of road links containing geometry information and road attributes. Intersections are usually not modeled in road network graphs. Despite, analysis results regarding roads or intersections are more expressive compared to those from road links.

On the other hand, the temporal dimension is another challenge. Traffic flows and, therefore, traffic states change frequently during a day and between the days of the week. Traffic state dynamics occur direction-specific and depend on different spatial structures of the network. Some patterns occur during morning peaks, others only at weekends and some occur more or

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than ACM must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from Permissions@acm.org.
IWCTS'18, November 6, 2018, Seattle, WA, USA
© 2018 Association for Computing Machinery.
ACM ISBN 978-1-4503-6037-1/18/11...\$15.00
<https://doi.org/10.1145/3283207.3283209>

less arbitrarily. Thus, spatio-temporal analysis of traffic states has to deal with specific spatial as well as temporal characteristics. The approach presented addresses the challenges mentioned to identify spatio-temporal traffic state patterns.

Besides spatial and temporal characteristics, the third main component for describing traffic patterns is the traffic quality itself. In a road network, the quality of the traffic flow gradually changes between “free flow” and “congested”. A common way to describe traffic states of a directional road section is the classification into so-called “level-of-services” (LOSs) [1]. LOSs are easy to interpret by humans and suitable for different road types. They describe free flow, delayed and congested states as clearly distinct and disjoint classes. Nonetheless, for traffic control, traffic prediction or transportation planning, sharp borders between LOSs do not reflect reality, because underlying measurements, as travel time or delay, are gradual variables. Thus, the strict binning into classes is more arbitrary and can irritate machine learning algorithms. For this paper, we propose a gradual adaptation (ratio scale) of LOSs (ordinal scale) to address the gradual change between free flow and congested. Such a traffic state description is more suitable for machine learning algorithms, because the scale of measure more likely represents reality, compared to an artificial binning. Consequently, the approach enables a more holistic technique for comparing traffic states between different road types and road topographies. The measure is used to analyze the traffic states of any arbitrary substructure of any road network. For proof of concept, the method is applied on common intersections of a nation-wide road network. Motorway exits are treated in the same way as simple or complex urban intersections with or without traffic lights.

The traffic state calculation is based on travel time, measured by probe vehicles. To obtain realistic free flow reference travel speeds for each link, the free flow reference travel speed is statistically calculated from historic probe vehicle data (PVD). Hence, the approach is entirely data-driven and does not rely on any traffic model. The qualitative and gradual LOSs are defined in a way that traffic information as travel time, travel speed, delay or delay rate are derivable from the traffic states.

The spatial analysis is based on self-organizing maps (SOMs) [2,3], an unsupervised learning approach. SOMs are usually used for clustering as well as feature reduction. Compared to other clustering methods (e.g. DBSCAN or k -means), SOMs are more suitable for gradual state variables, like the proposed traffic state measure. SOMs try to span the entire (traffic) state space with a two-dimensional neuron grid. Thus, they can recognize intermediate states or classes that could but do not occur. Furthermore, the location of a class within the neuron grid is an additional valuable information, as the location within a trained SOM is not arbitrary: Neighboring classes are more similar while the label of a k -means’ or DBSCAN’s cluster is random.

The basic idea is a combination of machine learning and visual analytics: For each intersection, one SOM determines its most common traffic states. Proper visualizations of a SOM’s neurons provide sufficient insights to understand traffic state patterns of complex intersections. In the next step, the temporal patterns are

determined by a frequency analysis of the cluster members. The results are visualized as heat maps.

The aim of analyzing traffic states is not new and has been tackled by different authors in the past [4–15]. The focus on temporal factors, which might influence traffic states, e.g. the weekday or daytime, is related to traffic prediction. Previous authors dealt with narrow focused prediction tasks such as predicting traffic states at (signalized) urban intersections [4–7] or motorway merging sections [8]. Such approaches are very specialized and different to holistic approaches as presented in this paper. In the following, we discuss holistic approaches aiming at analyzing network-wide spatial and/or temporal patterns.

Many previous approaches focused on network-wide travel time prediction. Lopez et al. [9] proposed an urban-wide prediction model based on clustering. The approach identified day-to-day regularities in urban congestions. The proposed 3D link speed map was an outstanding visualization to recognize the complex spatio-temporal relations. Similar concepts are presented in [10] for travel time analysis or [11–13] for congestion analysis in urban road networks. In all analyses, non-GIS or GIS-based visualizations were used to present and visualize identified traffic patterns. Necula [14] used 10,000 GPS traces from smartphones to identify urban roads that have the largest statistically significant relevance in traffic flow. The authors of [15] presented a spatio-temporal approach based on three LOS classes using a historical PVD dataset collected in an urban area to statistically identify congestion events and their spatio-temporal progress. In all works, the spatial clustering of the road network depended on similar traffic states only. In [11], the authors used a congestion level index as a form of gradual LOS. While this concept is similar to our proposed gradual LOS, the authors did not analyze the traffic of predefined road network subparts. They focused on network-wide spatial patterns but did not consider temporal patterns.

As spatio-temporal analysis method for detecting traffic patterns, the application of clustering algorithms is common. In [9] the authors used k -means and DBSCAN. Other authors applied statistical models [14,8,7], fuzzy fitting [4] and piece-wise linear curves [5]. Based on detailed research it can be assumed that there are currently no approaches that use self-organizing maps to identify spatio-temporal traffic patterns. The approach presented differs in other aspects. First, the approach does not distinguish between different intersection types, secondly, the analysis results are traffic states of real world entities called intersections and not of arbitrarily cut road links in a road network graph.

The approach proposed combines spatio-temporal clustering using SOMs with a visual analytics approach. In the following sections, we present data sources, data preparation and the clustering approach. The subsequent sections present the spatial and temporal analysis, the visualization of results and conclusions.

2 CLUSTERING APPROACH

For the identification of spatio-temporal patterns, unsupervised learning is a common approach. In this section we describe how a self-organizing map (SOM) is able to identify clusters of similar

traffic states of an arbitrarily selected substructure of a road network. While the training of the SOM is just an application, the extraction, coding and transformation of raw data to reveal plausible traffic state clusters that are reasonably interpretable from humans is the challenging aspect.

2.1 Data Sources

The clustering approach uses two main data sources, namely a digital road network and road- as well as direction-related traffic states. The road network is digitally represented as a road network graph. The road network graph is modeled as mathematical graph with edges and vertices. For this paper, Austria's official nationwide road network graph, called Graph Integration Platform (GIP.at), was used [16]. This graph consists of topologically connected road links attributed with several direction-dependent attributes as well as turn relations.

As exemplary route for the proof of concept, we selected a 13 km urban arterial road through the City of Salzburg, Austria, between two motorway exits "North" and "South" (Fig. 1). The route contains 18 intersections including motorway exits as well as roundabouts and simple or complex intersections (including ramps, sideways, grade separations etc.) with and without traffic lights (Fig. 2). Intersections were extracted from the road network graph by using an automated algorithm based on a qualitative spatial reference model [17]. This means that the algorithm automatically identified all road links belonging to one intersection. To simplify the digital representation of the intersection, the algorithm groups road links to inner sections (Fig. 1). Each inner section connects two inner nodes; and inner nodes are those points where more than two road links meet. If such an inner section has been modeled by several individual road links, the algorithm grouped the road links to one single inner

Figure 1: Exemplary route in Salzburg, Austria with 18 intersections. The detail view shows a complex intersection consisting of 52 road links. The 52 road links were grouped to 18 section-directions (different colors).

Figure 2: Different intersections: motorway exits: 1, 18; complex intersections without: 3, 10 and with traffic lights: 6, 7, 17; simple intersections with 2, 5, 11, 13, 14, 15, 16 and without traffic lights: 4, 12; roundabouts: 8, 9.

section. For each approaching road, the algorithm created an additional 200 m buffer for the outermost inner section. Finally, for each inner section and possible driving direction a so-called "section-direction ID" was created. For example, 'S-38933se' was the label for inner section 38933 and driving direction southeast. Driving directions of road links were expressed as cardinal directions using an 8-sector cardinal direction calculus [18]. The traffic states of these section-directions define the state vector (feature vector) of the intersection. The intersections in the example route have between 6 (simple T junction) and 40 inner sections (motorway exit "South"). The average is 12 and in total the route contains 220 section-directions.

An appropriate way to describe traffic states in a road network is to attribute directed road links with travel speeds, travel times, travel time delays or LOSs. Travel speeds, travel times and delays can be interpreted by humans since they are real value scaled. This supports interpretability, modeling and routing.

The Austrian Floating Car Data Testbed [19] collects travel times and speeds in near real-time from several thousand probe vehicles nationwide. On an average workday, the system receives around 30 million GNSS measurements, corresponding to 1.5 million road kilometers or 25,000 hours of vehicle movement data with typical sampling intervals between 1 and 30 seconds. Such high sampled probe vehicle data (PVD) enables the calculation of accurate delay information [20] as well as realistic travel times and speeds. For the pattern analysis, we used a one-year historical PVD dataset dated from July 1st 2016 to June 30th 2017. Each entry in the dataset contained travel time as well as speed being extracted from a single trip and referenced to a unique road link and direction. In order to prepare the data for further analysis, a

time-dependent and spatial aggregation was applied to obtain the traffic states for the road links of each intersection.

Concerning the temporal aggregation, daytime was split into 13 time slices between 7 am and 8 pm. For the one-year dataset this yielded $365 \times 13 = 4745$ unique time slices. PVD measurements between 8 pm and 7 am were not considered. Records with a speed value less than 0 or higher than 200 (outlier or data error) and not fully traversed road links (incomplete knowledge) were marked with “missing”. For each road link, all PVD measurements falling into the same time slice were averaged resulting in hourly mean speed values per road link.

The spatial aggregation summarized delay rates (see section 2.2) of road links belonging to the same section-direction. Thus, for a specific time slice and section-direction, the PVD’s travel speed value of each road links was required. Otherwise, the section-direction was marked with “missing” for this specific time slice. For example, if a section-direction consisted of three road links and only two of them had a measured travel speed value, they were not merged to a section-direction’s delay rate.

2.2 Data Preparation

Travel time and travel speed are not proper values for comparing different inner sections and/or different intersections. The qualitative interpretation of traffic quality depends on distinct spatial and traffic-related characteristics such as road classes, road topography or speed limits. It is more likely to define traffic quality by integrating information about travel speed that vehicles normally have on a specific road link. As it is common in transportation planning, we used v_{85} (85% percentile of all measured vehicles’ speeds) as realistic free flow reference speed for a road link. Such a speed reflects many parameters as radius, cross slope and visibility. The value was estimated from the one-year PVD dataset. Based on free flow reference speed v_{ref} , it was easy to define a traffic state value.

Let $d_{j,i}$ [s/m] be the delay rate of a road link i with the free flow reference speed $v_{ref,i}$ [km/h] belonging to section-direction j , and let v_i [km/h] be the observed (average) PVD travel speed on this road link, then $d_{j,i}$ can be determined with

$$d_{j,i} = \frac{3.6}{v_i} - \frac{3.6}{v_{ref,i}}. \quad (1)$$

The case $v > v_{ref,i}$ is handled by setting $d_{j,i} = 0$. Only the loss of time is expressed by the delay rate. The value 3.6 stands for the conversion between km/h and m/s. To get a delay rate per section-direction, the delay rates of single road links are combined. Let d_j be the delay rate [s/m] for section-direction j containing m road links with length l_i [m], and let $d_{j,i}$ be the delay rate [s/m] for these road links where $i \in \{1, \dots, m\}$. The section-direction delay rate d_j can be calculated with

$$d_j = \frac{\sum_{i=1}^m d_{j,i} l_i}{\sum_{i=1}^m l_i}. \quad (2)$$

If the sum in the numerator is not divided by the sum of the lengths, the received value describes the overall delay D_j of the

section-direction j in seconds. Travel time and delay are not a suitable choice for an intersection’s traffic state, because they depend on the length of each section-direction.

Nonetheless, looking closer at delay rate values, they still depend on reference speed v_{ref} (Fig. 3) relating to the inner section they belong to. For example, a delay rate of 0.1 s/m does not indicate the same traffic quality for different road types. While on urban roads, a delay rate of 0.1 s/m is not noticed by drivers, on a motorway it would be experienced as congestion. In addition, machine learning approaches have problems with the narrow band of free flow. Compared to congested state, free flow is underrepresented in the value range.

Instead of using delay rates, we defined the traffic quality as the percentage value (v/v_{ref}) of reached free flow reference speed. The thresholds for different level-of-services are commonly defined as percentage values. For example, the threshold 55% delimits the transition between “green” and “yellow” and 33% between “yellow” and “red” (Fig. 3 and 4). Using a gradual LOS concept (traffic quality is defined as $x\%$ of v_{ref}) results in the same numerical values, being independent of underlying free flow reference speed or travel speed. Despite, the ranges of the LOS classes were not equidistant. Green was defined for values between 100% and 55%, yellow between 55% and 33% and values less than 10% were close to stops. Such an unbalanced quality measure hampers a reasonable clustering. The goal was to obtain a rescaled traffic quality measure q based on the percentage of reached free flow reference speed to support the SOMs clustering ability. Therefore we proposed the following distance criteria: First, the distance between 100% and 55% (green) and 55% and 10% (non-green) should be numerically equal. Second, the distances between 100% and 77.5% (middle of “green”), between 77.5% and 33% and between 33% and 10% should be numerically equal (Fig. 4). In order to derive such a measure for the interval between 100% and 10%, we applied a logarithmic transformation first and a square root afterwards.

$$\begin{aligned} q_j &= (\log_{2.2727}(d_j * v_{ref,j}/3.6 + 1))^{0.5} * 1.7913 \\ &= (\log_{2.2727}(v_{ref,j}/v_j))^{0.5} * 1.7913 \end{aligned} \quad (3)$$

The square root stretches the values between 0 and 1 and shrinks values greater 1 after applying the logarithm. To shrink and stretch the right value ranges, we defined the mid of yellow (44%) to be at the “stable” value 1.0, i.e. $\log_b(1/0.44) = 1.0$, which holds for $b = 2.2727$. The final scaling factor 1.7913 maps the values between 100% and 10% on the interval from 0 to 3. The proposed transformation stretches the small green and yellow band and balances the different traffic states. This enabled the clustering algorithm to cluster all traffic states equally balanced and avoided overrepresentation of single traffic states. The arbitrary selected target interval between 0 and 3 did not affect the clustering. It was applied for aesthetic reasons.

Finally, the vector of all section-direction values of q defined the traffic state vector of the intersection (feature vector). These values were comparable between different road types, road topographies and speed limits. Hence, it was an appropriate input for the succeeding SOM clustering.

Figure 3: Delay rate d and its qualitative interpretation depends on the free flow reference speed v_{ref} of the traversed road.

Figure 4: Selected scaling of proposed traffic quality measure q (without unit). The horizontal lines outline different percentage steps of reached free flow reference speed (v/v_{ref}). The grey lines show examples of travel speeds v and its non-linear relation to quality measure.

2.3 Training Self-organizing Maps

After defining the intersection's traffic state values, different spatio-temporal patterns were identified by clustering. Thus, a self-organizing map (SOM) was trained for each intersection. Each SOM clustered the intersection's traffic state vectors into s clusters, where s was equal to the number of neurons of the SOM. The columns of the training dataset contained the section-directions of the intersection; the rows contained the 365×13 time slices. For each time slice and section-direction, the rescaled

delay rates q described the traffic state at the corresponding inner section for each driving direction.

Outlier, data errors, incomplete or not traversed road links caused many missing values in the training dataset. This is a common problem when working with real-world measurements such as the ones from PVD. Some SOM implementations have the ability to treat "at least some" missing values in the training dataset. Yet, permitting too many missing values decreases the quality of the clustering because they do not contain information. On the contrary, a restrictive missing value policy leads to the loss of many input vectors and results might lose expressiveness as well. The right balance of allowed missing values was determined by considering the cumulative distribution function (CDF) of the percentage of allowed missing values per column and per row separately. For the 18 intersections of the example route, the maximum of $1/3$ of missing values balanced between losing too much samples and including too many missing values. The CDF plots show a kind of knee close to the $1/3$ value. Increasing the value would add numerous missing values, but would not increase the number of samples dramatically. The threshold considered rows and columns. If a section-direction (column) contained more than 33.3% of missing values, the section-direction was not considered. For example, this was the case for very rarely traversed motorway ramps (cf. Fig. 13). If a time slice (row) contained more than 33.3% missing values, the time slice was rejected. The filter was applied as follows: First, all section-directions with more than one third of missing values were removed. Then, the rows with more than one third of missing values were removed as well. Removing data in this order yielded more training data even though more attributes were dismissed. For the 18 intersections, this filtering yielded training datasets between 70% and 90% of all 365×13 time slices. After this step, the training dataset T_k for intersection k was ready for training.

Different intersections consist of different numbers of section-directions respectively traffic states. This fact was treated by adapting the SOM's size on the amount of available training data and the size of the state vector. For practical reasons the size should be a squared number $s \times s$. Let n_k be the number of time slices (training samples), m_k the number of section-directions (state variables or features) in the training dataset (matrix) T_k for intersection k . The value $n_{max} \in \mathbb{N}$ with $n_{max} \geq 2$ provides an upper bound. We choose the appropriate SOM size as s^2 with

$$s = \min([n_k], [\sqrt{m_k}], n_{max}). \quad (4)$$

Since the training data was approximately the same for each intersection but the number of included section-directions differed, s was determined by the number of available section-directions in all cases. Nevertheless, it is not reasonable to define s^2 clusters with less than s^2 input vectors. Therefore, it was more of a precautionary measure to add $[n_k]$ to the formula. Adding the parameter n_{max} allowed a manual maximum for the SOM size because in some cases an intersection contained many section-directions (motorway) leading to a high number of clusters. In one trial n_{max} was set to 3. The resulting SOMs were either of size 2×2 or 3×3 . In another trial 4×4 SOMs were allowed as well

for intersections with enough section-directions. Larger SOMs were found to be hard to interpret in their temporal patterns (see section 3.2).

For the training of the SOMs, we used the R package *kohonen*. The SOMs were trained with the included function *sommap*. This training function accepted datasets including missing values by specifying an acceptable missing value ratio for rows and columns. The result of the training was a $s \times s$ matrix with $s \times s$ neurons (Fig. 5). Each neuron represented a cluster and each cluster contained similar traffic states of an intersection. The advantage of SOMs is that SOMs exploit the full state space given by all samples. If the SOM contains only a few neurons, as in this case, each neuron represents an existing state and therefore contains at least one sample. SOMs try to span state

Figure 5: Intersection 9, roundabout: trained 3×3 SOM of the intersection. The color represents the number of samples falling in each cluster. 4240 samples (89%) were selected for training.

Figure 6: Intersection 9, roundabout: state representation (black line) of neuron 1. The neuron/cluster represents 293 samples/time slices of the one-year dataset. The ordinate shows the traffic quality measure q . The yellow, red and dark red line represent 55%, 33% and 10% of v_{ref} threshold (see Fig. 4).

space with their 2-dimensional hexagonal map. Neighboring neurons represent more similar states than distant. Thus, SOMs provide a kind of feature reduction too. The coordinate of a neuron can be used as an input for a succeeding higher level

clustering. Fig. 5 shows how the input data spreads among the map/clusters. The colors give an approximation of how many samples/time slices fall into which cluster. Fig. 6 is a plot of neuron's weights. The weights represent the states of the intersection, and the states are defined by the quality measure values of the section-directions. Thus, the clustering regards spatial traffic patterns, but the patterns are not recognizable in both visualizations. The artificial quality measure is not directly interpretable and the order of the section-directions is arbitrary and does not correspond with the topological shape of the intersection. Finally, there is no information about time-dependent regularities, as "cluster 1 represent a morning peak pattern of a common working day".

3 VISUALIZATIONS AND PATTERNS

The results of the SOM clustering are not directly interpretable. Neither spatio-temporal patterns nor specific traffic states are recognizable. The exemplary visualizations of this section fill this gap. They outline the spatial and temporal patterns as well as provide interpretability. First, a GIS-like visualization of SOM's states provides insights into spatial regularities of traffic states. Second, a succeeding heat map outlines the temporal regularities by presenting relative frequencies.

3.1 Visualization of Spatial Patterns

In order to facilitate interpretability of SOMs, and to recognize spatial traffic patterns, two different visualizations were proposed. Fig. 6 shows a slight adaptation of a SOM's neuron plot. A raw neuron plot contains only the black line representing the neuron's weights. The weights define a representative "mean state" for the cluster. For the presented traffic state analysis, the weights represent the traffic quality measure q for all section-directions. In Fig. 6 the additional yellow, red and dark red line as well as the colored dots encourage interpretability of the traffic states. For example, Fig. 7 outlines the different possible traffic states. Traffic states with a reduced traffic flow are clearly recognizable (left column) and distinct to the free flow state (top right). The colors of the dots represent a gradual interpretation of the LOS concept. In traffic information systems, the LOS values "green", "yellow" and "red" represent free flow, delayed and congested. A color ramp interpolates between these three classes. To get balanced and smooth transitions between the color steps, the color ramp was generated for the rescaled range of the traffic quality measure (Fig. 4).

By using the geometry information of road links, the neuron's weights are visualized in their topographical relation (Fig. 8). This spatial GIS-like visualization colors each inner section using the same gradual LOS color ramp. Delay rate, delay, travel speed and travel time complete the information. All values can be calculated using inner section's free flow reference speed v_{ref} and length l because the functions in equation (1) to (3) are bijective. That means that the gradual traffic quality measure q is fully reversible to common values and units. Fig. 9 shows the topology plots of all neurons. Delayed states are on the left, the free flow state top right. The plot shows the range of intersection's traffic states that

Figure 7: Intersection 9, roundabout: neuron plots of all 9 neurons. More delayed states are on the left. The free flow state is at top right.

Figure 8: Intersection 9, roundabout: topology plot of neuron 1. The neuron represents a traffic state where both inbound roads at the bottom and the outbound road in the top middle are delayed. Both outbound roads at the bottom are close to free flow.

Figure 9: Intersection 9, roundabout: topology plots of all neurons. More delayed traffic states are on the left. The free flow state is at top right (cf. Fig. 7).

actually appear. The traffic states of inbound and outbound roads are clearly distinct. This figure shows another interesting feature of SOMs. The states are not arbitrarily distributed in the map, because during training the SOM tries to span the state space with its 2-dimensional (hexagonal) grid structure. Similar states are adjacent and closer together than more distant.

Neuron plot and topology plot outline spatial patterns of an intersection's traffic states. The recognition of delayed, not delayed and congested inner sections is possible. The remaining question is, whether there are temporal regularities too.

3.2 Visualization of Temporal Patterns

For the temporal analysis, we focused on the temporal dimensions of the days of the week and daytime. Both dimensions were selected a-priori. Nevertheless the search for other temporal regularities is possible, e.g. regularities in season or before long weekends. Any classification function that bins time and/or date into classes is applicable. For example, weekends during holidays or the daytime before sport events are other reasonable temporal categories to search regularities.

From a mathematical perspective, we calculate an n -dimensional relative frequency matrix for each cluster separately. At least for one to three dimensions, heat maps are a human interpretable visualization. Each tile of the heat map visualizes the percentage of samples falling into the specific combination of the day of the week and daytime (Fig. 10). Heat maps foster the recognition of regularities by considering the arrangement of tiles representing high or low values. The heat map from Fig. 10 shows the temporal occurrence of the traffic state represented by neuron 1 (Fig. 8). This traffic state occurs more frequently on weekdays during afternoon and does not occur on weekends and evenings (> 18 pm).

Fig. 11 enables the comparison between all neuron's heat maps. The plot shows a clear distinction between weekend (top right) and weekday (bottom left) traffic states. There are also some intermediate states and some states for afternoon and morning peaks. Neuron 2 (top middle) presents a more or less arbitrary state with a tendency to the time between 9 am and 5 pm. Even in this case, the interpretation "this state does not depend on daytime and the day of the week" provides insights. Looking closer at the traffic states, neuron 2 represents a delayed traffic in the direction to the city center. This state can obviously occur at any time. It is also possible to compare the number of samples falling in each cluster. The bottom left state "usual weekday" occurs most frequently (813/4240). All strongly delayed states (left column) represent 36% (1546/4240) of all samples. Hence, congested states are very common at this intersection. Moreover, with an alternative calculation of relative frequencies, it would be possible to understand which traffic state is most likely for a specific day of the week and daytime. In this case, the matrix contains the relative frequencies calculated for each tile of the heat map separately. The resulting plot would enable interpretations like "On Mondays at 10 am the state of neuron 1 occurs in 12% of all Monday 10 pm samples".

Figure 10: Intersection 9, roundabout: heat map of neuron 1. The color represents the relative frequency (0% white, dark blue 100%). Neuron 1 represents a common traffic state in weekdays' afternoons. The state is very unusual during evenings and weekends.

Figure 11: Intersection 9, roundabout: heat maps of all neurons.

3.3 Other Types of Intersections

The example route contained 18 intersections (Fig. 1, Fig. 2). In the previous sections, we discussed an inner city roundabout (intersection 9) with 9 section-directions to outline possibilities and interpretations of the spatio-temporal clustering. Generally, the approach was not restricted to roundabouts. Other intersection types, e.g. motorway exits or complex intersections with and without traffic lights, had the same parameter setting.

For example, intersection 18 or motorway exit “North”, respectively, represented an intersection between a motorway and a major federal road. At this intersection there was a heavy inbound traffic load caused by commuter traffic. Intersection 18 consisted of 38 section-directions and spanned an area of 2,300 m × 1000 m. For the clustering, 32 section-directions were selected. The missing value constraint excluded 6 section-directions. The missing dots in Fig. 12 and the gray section-directions in Fig. 13 indicated discarded sections. For the training of the 3 × 3 SOM, 4280 samples remained in the training dataset. The neuron plots in Fig. 12 show several “very similar” traffic states close to free

flow. Some of them have a kind of zigzag pattern in the second part. This was caused by the section-direction's order. An alternation between both driving directions of a single section-direction caused the traffic state alternation. A detailed look identified the zigzag as outbound traffic on the federal road at weekends. Two traffic states (bottom right) showed remarkable congestions. Both outline congestions on the motorway but the driving direction was different. Four states (top right corner) show a minor delay at the end of the state profile. The topology plots explain this observation. Fig. 13 shows the lower two neurons in the right column. Neuron 6 (top) represented an inbound commuter traffic. Together with the increased traffic flow coming from the motorway exit, the subsequent road section showed a delay. Fig. 14 designates this traffic state as a common morning peak pattern on weekdays. With an n of 789, the pattern was the rule rather than the exception. In contrast, the traffic state of neuron 9 (bottom) shows a congestion on the motorway with effects on the ramp. This state occurred before weekends on Thursday late afternoon or on Friday afternoon. It rarely occurred (92 times in one year). Also all other heat maps showed clear distinct temporal occurrence. In addition we trained a 4 × 4 SOM. The results were very similar. The neuron and topology plots showed more intermediate states. For instance, the motorway congestion (Fig. 13) was split into two states. One almost equal state and one state with yellow color, which was an actually occurring intermediate state. Most of the states in the 4 × 4 SOM were almost free flow states.

Figure 12: Intersection 18, motorway exit: neuron plot of all neurons.

The second example shows intersection 10, a complex inner city intersection without traffic lights. This intersection represents a known bottleneck in the road network. The results of the analysis presented a very diverse set of traffic states (Fig. 15, Fig. 16) with distinct temporal patterns (Fig. 17). This intersection was more congested than others. During the week, almost every possible congestion pattern occurred. The free flow state was at top right and was reached mainly at weekends. The weekday traffic states are at the bottom left. It is recognizable that

Figure 13: Intersection 18, motorway exit: topology plot of two exemplary neurons (bottom right in Fig. 12).

Figure 14: Intersection 18, motorway exit: heat map of all neurons.

Figure 15: Intersection 10, complex intersection: neuron plot of all neurons.

the congestions at weekdays did not occur at weekends. Thus, there was a very distinct change of traffic flow between weekday and weekend. The grey sections in Fig. 16 were discarded section-directions. The road section connected a residential area. Hence, the traffic demand was low and the road links were rarely traversed by probe vehicles.

4 CONCLUSIONS

The previous results have shown that the approach proposed can successfully be applied to identify spatio-temporal traffic patterns for different types of intersections. The extracted spatial as well as temporal patterns were plausible and regularities were clearly observable and reflected the specific circumstances of intersection characteristics. First, the SOM's clustering segregates the different spatial patterns by considering the state variables. Second, feature maps presented probability estimations for temporal patterns that occurred or did not occur at a specific time. Patterns without any temporal regularity indicated that the pattern occurred arbitrarily or the cause was not expressed by the presumed temporal categories. To foster these interpretations, it was crucial to provide interpretable visualizations interpretable by humans.

Identifying regular and irregular spatio-temporal patterns in a spatial network structure, e.g. a road network with traffic states, is a challenging task. (1) One precondition is a proper grouping of the structure to reasonable topological entities. In our examples, an automated algorithm grouped the digital road links to inner sections of an intersection. The grouping minimizes the states of an intersection and facilitates interpretability. (2) Another challenge was the treatment of missing values. Probe vehicle data do not necessarily provide a complete traffic state at any snapshot. However, SOMs were able to treat missing values if they were not too numerous. (3) The numerical representation of the inner states has to be designed in a proper way: The aim of the learning task is to produce plausible clusters. For example, for the application proposed, the traffic states should be interpretable and expressive. Hence, a suitable state measure has to (3a) describe the states qualitatively, otherwise the expressiveness decreases. The measure (3b) has to be applicable for the comparison between all inner structures. For instance, the numerical values have to express the same meaning for all road types, road topologies and speed limits. Finally, the measure (3c) is a similarity measure and reflects the human understanding of resemblance. For example, the suggested gradual LOS values provided these abilities. Using just raw values for travel time, travel speed or delay rate did not exploit all possibilities of unsupervised learning.

Finally, there were some interesting perspectives for adaptations of the approach. First, our examples outlined patterns regarding daytime and the days of the week. An additional optimization task for temporal pattern extraction could automatically search the most expressive time categories. Second, the neuron's SOM coordinates could be used as an input for a higher-level traffic state analysis. For example, intersections

Figure 16: Intersection 10, complex intersection: topology plot all neurons.

Figure 17: Intersection 10, complex intersection: heat map of all neurons.

grouped to a higher-level road network structure could represent a city district. The coordinates of the lower-level clusters' neurons could be used as the state vector of the higher-level SOM. This idea is close to the idea of convolutional neural networks, a deep learning approach. Each succeeding layer in a multi-layer architecture provides patterns that are more complex. Third, the estimated probabilities from the temporal analysis could be utilized for long-term forecast. For a specific daytime and day of the week, the state of the cluster with the highest probability would be the choice for forecast. The status vector of the cluster chosen defines travel time, travel speed, delay and delay rate of all sections at the intersection.

ACKNOWLEDGMENTS

This work was partly funded by the Austrian Federal Ministry for Transport, Innovation and Technology.

REFERENCES

- [1] HCM. 2000. Highway Capacity Manual. *Transportation Research Board, National Research Council*. Washington, D.C., USA.
- [2] Kohonen, T. 1995. Self-Organizing Maps. Springer.
- [3] Andrienko, G., Andrienko, N., Bremm, S., Schreck, T., Von Landesberger, T., Bak, P. and Keim, D. 2010. Space-in-Time and Time-in-Space Self-Organizing Maps for Exploring Spatio-temporal Patterns. *Computer Graphics Forum*. 29, 3, 913–922.
- [4] Tang, L., Kan, Z., Zhang, X., Yang, X., Huang, F. and Li, Q. 2016. Travel time estimation at intersections based on low-frequency spatial-temporal GPS trajectory big data. *Cartography and Geographic Information Science*. 43, 5, 417–426.
- [5] Ban, X. (Jeff), Herring, R., Hao, P. and Bayen, A.M. 2009. Delay Pattern Estimation for Signalized Intersections Using Sampled Travel Times. *Transportation Research Record*. 2130, 1, 109–119.
- [6] Liu, X., Lu, F., Zhang, H. and Qiu, P. 2012. Estimating Beijing's travel delays at intersections with floating car data. *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Computational Transportation Science - IWCTS '12*, 14–19.
- [7] Zhu, J.Z., Cao, J.X. and Zhu, Y. 2014. Traffic volume forecasting based on radial basis function neural network with the consideration of traffic flows at the adjacent intersections. *Transportation Research Part C: Emerging Technologies*. 47, 139–154.
- [8] Elefteriadou, L., Roess, R.P. and McShane, W.R. 1995. Probabilistic nature of breakdown at freeway merge junctions. *Transportation Research Record*. 1484, 80–89.
- [9] Lopez, C., Leclercq, L., Krishnakumari, P., Chiabaut, N. and van Lint, H. 2017. Revealing the day-to-day regularity of urban congestion patterns with 3D speed maps. *Scientific Reports*. 7, 1.
- [10] Lopez, C., Krishnakumari, P., Leclercq, L., Chiabaut, N. and Lint, H. Van 2017. Spatio-temporal partitioning of transportation network using travel time data. 14 p.
- [11] Rempe, F., Huber, G. and Bogenberger, K. 2016. Spatio-Temporal Congestion Patterns in Urban Traffic Networks. *Transportation Research Procedia*. 15, 513–524.
- [12] Saeedmanesh, M. and Geroliminis, N. 2016. Clustering of heterogeneous networks with directional flows based on “Snake” similarities. *Transportation Research Part B: Methodological*. 91, 250–269.
- [13] Cheng, T., Tanaksaranond, G., Brunsdon, C. and Haworth, J. 2013. Exploratory visualisation of congestion evolutions on urban transport networks. *Transportation Research Part C: Emerging Technologies*. 36, 296–306.
- [14] Necula, E. 2015. Analyzing Traffic Patterns on Street Segments Based on GPS Data Using R. *Transportation Research Procedia*. 10, 276–285.
- [15] Xu, L., Yue, Y. and Li, Q. 2013. Identifying Urban Traffic Congestion Pattern from Historical Floating Car Data. *Procedia - Social and Behavioral Sciences*. 96, 2084–2095.
- [16] Mandl-Mair, I. 2012. GIP.at: The Basis for a Modern Administration of Austria's Transport Routes. *Proceedings of the 19th ITS World Congress*, Vienna, Austria.
- [17] Rehl, K., Brunauer, R., Gröchenig, S. and Lugstein, E. 2017. Generation of Meaningful Location References for Referencing Traffic Information to Road Networks Using Qualitative Spatial Concepts. *Progress in Location-Based Services 2016*. Springer, 173–191.
- [18] Frank, A. U. 1991. Qualitative spatial reasoning with cardinal directions. *Proceedings of the 7th Austrian Conference on Artificial Intelligence*, Springer, 157–167.
- [19] Rehl, K., Brunauer, R. and Gröchenig, S. 2016. Collecting floating car data with smartphones: results from a field trial in Austria. *Journal of Location Based Services*, 10(1), 16–30.
- [20] Brunauer, R. and Rehl, K. 2014. Deriving driver-centric travel information by mining delay patterns from single GPS trajectories. *Proceedings of the 7th ACM SIGSPATIAL International Workshop on Computational Transportation Science - IWCTS '14*, 25–30.