Classification of street junctions according to traffic regulators

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Abstract

This paper proposes a method of classification of street junctions according to traffic regulators by using opportunistically collected vehicle trajectories. The vehicular traffic at an intersection is regulated through a set of traffic rules or controls: either in form of traffic signals or traffic signs/rules that influence driving decision processes according to the current traffic. At such regulated areas the observable movement of vehicles is affected by these rules, with the most commonly observed movement pattern being the moderation of the driving speed due to decelerating and/or stopping on account of a traffic regulation. In this work, we explore the idea of sensing traffic regulators in form of traffic lights and priority/yield controls by learning in a supervised way the associated speed profiles at such regulated locations. More specifically, we explore and assess different settings of the feature vector used to train a classifier for detecting movement patterns in in-vehicle sensor data-streams, containing highly accurate speed readings that are obtained from vehicles' CAN-BUS in addition to their GPS location. The results show high Recall for prediction of traffic light category and relatively low Precision and F-measure. We discuss possible explanations and solutions as further step of this research.
Keywords: traffic regulators; traffic signs; movement pattern; speed profile.

1 Introduction

The time-ordered locations of a moving object obtained as sequences of GPS recorded logs compose spatiotemporal trajectories that contain implicit knowledge of objects' movement regarding the underlying movement patterns and structure, which when identified can be applicable in various areas (Sester et al. 2012). Junctions are locations which are geometrically complex and due to this reason traffic participants need to coordinate their actions for safely crossing them. Such a mean of traffic coordination in junctions are traffic rules/regulators. There are in-situ traffic rules materialized as physical objects (traffic signs) as well as global/general traffic rules such as the right-way priority rule. Those traffic controls obviously affect the movement behaviour of the objects. In this paper, we detect traffic rules/regulators by observing and interpreting the movement behaviour of vehicles through the recognition of movement patterns along their driving paths. Hence, the research presented in this paper concerns the problem of classification of junctions based on their control type by analysing the collective movement behaviour of drivers.

Crowd-sourcing traffic regulation information has many benefits, as traffic rules are important components of maps considering the advances in autonomous driving. Self-driving cars need HD maps, up-to-date and detailed and traffic rules without doubt contribute in this domain. Maps containing such information can conduce to driving safety (Zourlidou and Sester 2015a, 2015b) by assisting the drivers to regulate their driving behaviour according to the traffic rules through Advanced Driving Assistance Systems (ADAS). One example is the estimation of drivers' context awareness and the issue of relevant warnings (Armand et al. 2013).

2 Junction classification accordint to traffic controls

In the following subsection 2.1, we shortly describe the existing approaches in the area of traffic regulator detection, whereas in 2.2 we thoroughly explain our novel method.

2.1 Existing methods

Pribe and Rogers (1999) propose a method that uses an 11-input-neuron Neural Network (NN) for learning to associate the driver behaviour with a subset of traffic controls: stoplights and stop signs. As input features they use the average and standard deviation of the number of times that vehicle stops, the total duration of all stops and the durations of the three stops closest to the end of the segment. They also compute the percentage of traversals that included at least one stop for each segment.

Palma et al. (2008) modify the widely known clustering algorithm DBSCAN by implementing a speed-based spatio-temporal clustering method (CB-SMoT) for detecting important places, distinguished by the stop duration of nearby subjects. The authors mention the adequacy of their method for the problem of traffic control detection (e.g. stop signs), though without providing relevant experimentation and results.

Carisi et al. (2011) propose a simple method to enrich digital maps with the location and timing of stop-signs and traffic lights using a small number of traces per road segment. The method is reported as successful when spatiotemporal data from crowd-source platforms, such as OSM, was tested for their applicability on this objective.

Hu et al. (2013) describe a supervised approach (Random Forest classification) as well as an unsupervised method

(Spectral clustering) for a 3-class classification of junctions (stop signs, traffic lights and uncontrolled junctions). Both methods use a physical feature vector (final stop duration, minimum crossing speed, number of decelerations, number of stops, and distance from intersection) and a statistical one (minimum, maximum, mean and variance of the physical feature values) for describing the crossing behavior of intersections.

Mozas-Calvache (2016) focuses on traffic limits by comparing the traffic regulator and the observed drivers' behavior at an area using VGI data, i.e. differences between the speed limit and observed speed when crossing that area.

More recently, Wang et al. (2017) identify traffic rules in the form of time-varied permission and prohibition of U- and left-turns by clustering the number of trajectories passing through an intersection and analysing the change of the crossing pattern along the time.

This paper explores the effects of high-quality speed profiles in terms of both accuracy and temporal resolution as features for a classifier trained to distinguish between traffic light controlled and priority/yield controlled junctions. In the following section a detailed description of the method is given.

2.2 Learning traffic regulators

Our approach is based on the observation that in real-life traffic, different traffic regulators cause vastly different driving behaviour: for traffic lights vehicles have to come to a full stop when the traffic light is red, while during green-light phases, the cars can cross more or less unhindered by other vehicles. In priority/yield control areas, vehicles from roads with right of way priority can cross mostly unhindered all the time, while vehicles from roads without right of way need to stop to give way at irregular times, depending on the traffic along crossing roads. In all these cases, characteristic is the moderation of vehicles' speed and for this reason we selected to use speed as a means of distinguishing different traffic regulators.

2.3 Speed profiles as learning features

In Figure 1, on the left plot, we show two different ways for looking at the speed of a vehicle approaching a junction: the left graph gives an example of a vehicle's speed over the last 60m before a traffic light regulated intersection. From 60m to 21m from the junction, the speed constantly increases from 5km/h to 38km/h and stays a bit of over 35km/h until crossing junction center (0m). In the right plot, we show the speed of the same vehicle at same junction, crossing over the last twenty seconds before crossing the junction. Here we can see the vehicle decreasing its speed while approaching the junction until it comes to almost a standstill nineseconds away from the junction center. Then it starts accelerating similarly to left plot. This example highlights the strengths of each

Figure 1: Two different ways for defining speed profiles of a vehicle (plots corresponds to the same junction crossing). Depicted are the last 60 meters (left, speed-over-distance) and the last 20 seconds (right, speed-over-time) before crossing a traffic-light controlled junction.

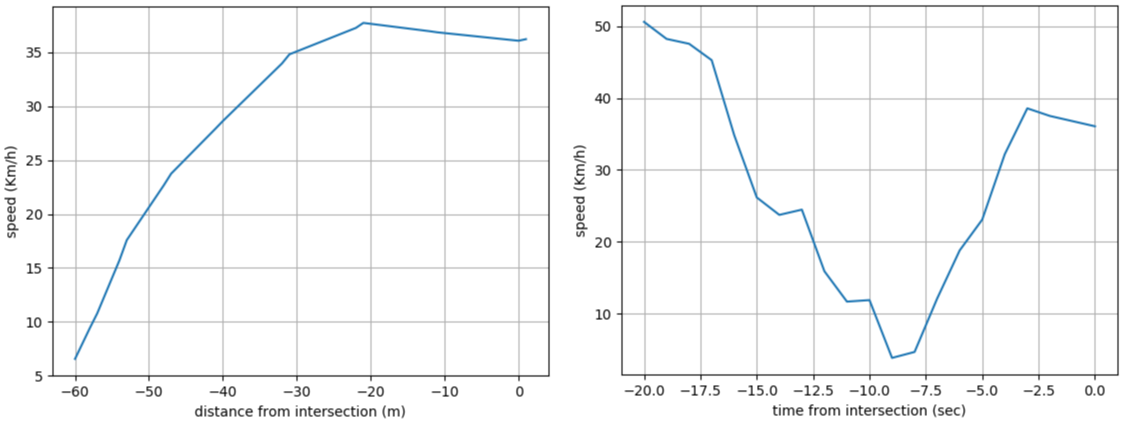


Figure 2: Spatial (top) and temporal segmentation (bottom) of a trajectory. Sl meters (Tl sec) before the junction and Sr meters (Tr sec) after the junction are segmented, respectively, into k and n equidistant segments. The speeds at these k+n+1 locations make up the feature vector of the classifier.

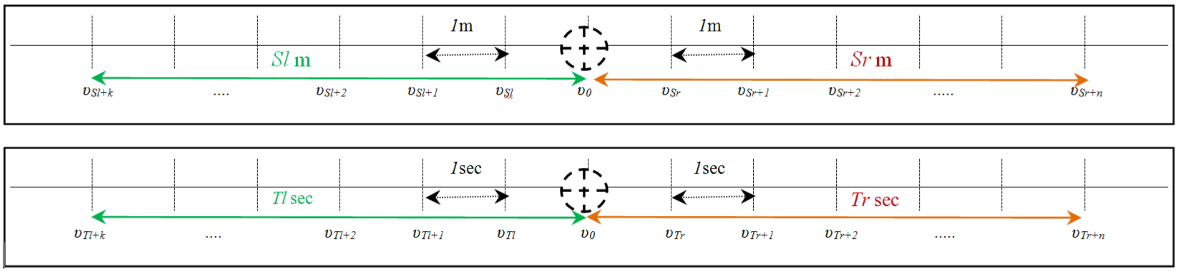
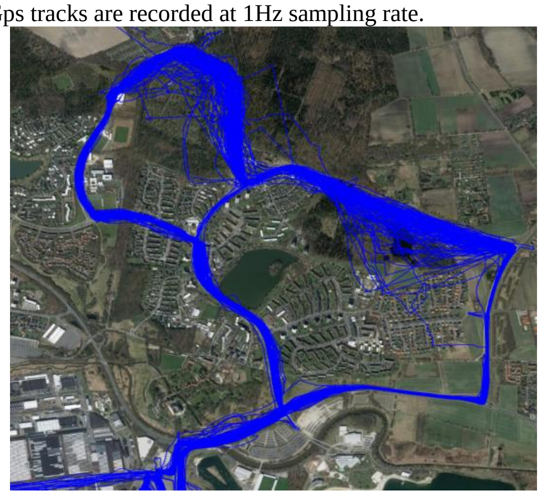


Figure 3: A snapshot from the dataset at the area of study. Gps tracks are recorded at 1Hz sampling rate.



speed profile definition. Both are of constant-legth and both contain speed related information but at different resolutions and domains. One focuses on spatial features (better spatial resolution) and the other on time (better temporal resolution).

The proposed method makes use of the information that temporal and spatial speed profiles embody by using them as features of a classifier that is trained to recognise traffic light controlled and priority/yield controlled junctions. In the next section we explain in detail how we construct the speed profiles, prosposing different variations for experimentation.

2.4 Dataset and classification

We used a set of opportunistically collected gps tracks (1Hz sampling rate) as well as speed readings from vehicles' CAN Bus, recorded at a city in Lower Saxony, Germany. The trajectories as shown in Figure 3, sample 31 junctions, 25 of which are priority/yield controlled and six are traffic lights. The ground truth map of the junctions, as shown in Figure 4, was constructed with on site examination.

We build a classifier (C4.5 (J48) decision tree), based on the speed profiles of the vehicles that cross these locations that can distiguise traffic light junctions from priority/yield junctions.

As feature vector for learning/testing of the classifier we used speed measurements obtained from vehicles CAN-Bus. We tested two types of speed profiles: one where the speed samples are equidistant (1m) along a fixed-length spatial interval before the geometric intersection centre and the other along a fixed-length temporal interval respectively (sample equidistant at 1sec). For example, selecting a fixed spatial interval of 50m (Sl meters, in top Figure 2) before the junction center and 50m (Sr meters, top Figure 2) after the junction center, we have a speed profile of 101 speed records, each of them 1m spatially distant from the nearby. Similarly are constracted the speed profiles at temporal intervals (bottom Figure 2). The effect of the selected interval lengths (spatial/

Figure 4: Ground truth map of the area of study: traffic lights (blue), traffic light pedestrian crosses (black), traffic light operated through sensor for vehicles that enter highway from a parking lot (green), yield/priority signs.

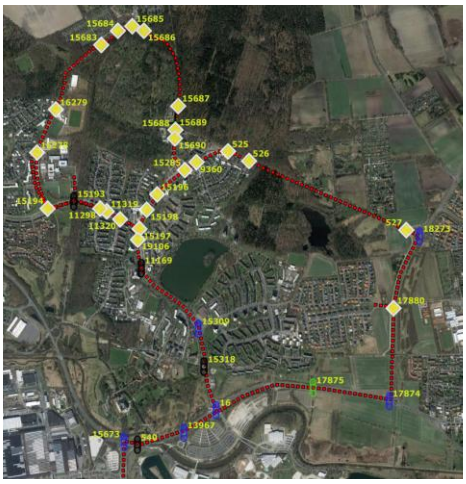
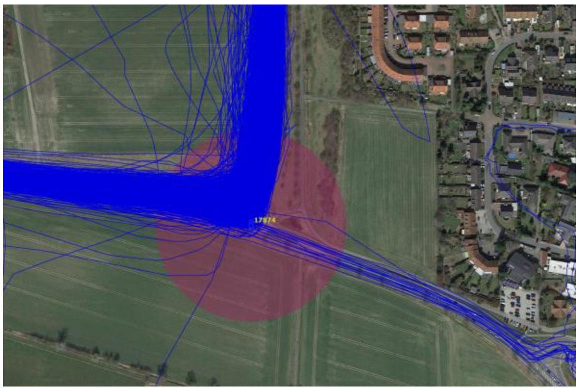


Figure 5: A buffer around each junction was created and the labels within the buffer were counted.



temporal distance from junction center) on the classification is reported and discussed in the next paragraphs.

The classifier was trained at junctions of different regulation controls assigning uniformily the same label for all trajectories that cross a junction of certain type of regulation. For testing, each GPS sample along a trajectory and the associated segment (Sl m before and Sr m after the trajectory point) was classified and the resulting label stored at the current GPS position.

For evaluating the classification results, we created buffers of different sizes around the junctions of the area of study (Figure 5), counted within them the labels from different categories and computed the total number of each label (1 for each trajectory) over the total number of trajectories that cross the buffer. We assign as label of a junction the one with the highest percentage of predicted labels: **max** $\left\{\frac{Total\ \#label1}{\#trajectories}, \frac{Total\ \#label2}{\#trajectories}\right\}$.

Table 1: Confusion matrices, Recall, Precision and F-measure for different experimentations on feature vector (segmentation settings) and evaluation (buffer size)

Spatial Segment.	-30m, 0m				-50m, 0m				-60m, 0m				-50m, 50m			
Buffer size	30m		50m		30m		50m		30m		50m		30m		50m	
Confusion Matrix	6	19	6	19	5	15	6	18	5	16	6	17	6	18	6	17
	0	4	0	4	1	8	0	5	1	7	0	6	0	5	0	6
Recall	**1**		**1**		0,83		**1**		0,83		**1**		**1**		**1**	
Precision	0,24		0,24		0,25		0,25		0,24		**0,26**		0,25		**0,26**	
F-measure	0,387		0,387		0,307		0,4		0,372		**0,413**		0,4		**0,413**	
Temporal Segment.	-6sec, 0sec				-8sec, 0 sec				-10sec, 0sec				-15sec, 0sec			
Buffer size	30m		50m		30m		50m		30m		50m		30m		50m	
Confusion Matrix	5	14	6	15	5	13	5	13	6	16	6	17	5	16	6	16
	1	9	0	8	1	10	1	10	0	7	0	6	1	7	0	7
Recall	0,83		**1**		0,83		0,83		**1**		**1**		0,83		**1**	
Precision	0,26		0,28		0,18		**0,31**		0,27		0,26		0,24		0,27	
F-measure	0,396		0,436		0,296		**0,451**		0,425		0,413		0,372		0,425	

3 Experiments and evaluation

On Table 1 are shown the results of different experimentations on feature vector and evaluation settings. For spatial segmentation of trajectories, we tested four combinations of before-after intersection spatial intervals, i.e. (-30m,0m), (-50m,0m), (-60m,0m), (-50m,50m) and for temporal segmentation another four, (-6sec, 0sec), (-8sec, 0sec), (-10,0sec), (-15,0sec). Also, we used two different buffer sizes, 30m and 50m. Observing the confusion matrices (positive for traffic light and negative for priority signs), we can see that although traffic lights are correctly predicted in most of cases, same time there are many false positive. For example for (-30m,0m) spatial segmentation and buffer=50, all traffic lights are correctly predicted (TP=6), but 19 priority signs are misclassified as traffic lights (FN=19), and only four yield signs are labeled correctly (TN=4).

We can also observe the same pattern we observe for other settings, resulting in a high *Recall* (TP/(TP+FN)) and low *Precision* (TP/(TP+FP)) of the classification. According to the *F-measure*, better performance was found under temporal segmentation (-8sec,0sec) and buffer 50m, with *Recall* 0.83, Precision 0.31 and F-measure 0.451. For spatial segmentation, the best classification result was found for (-60m,0m) and (-50m, 50m), using buffer 50m and resulting to *Recall* 1, *Precision* 0.26 and *F-measure* 0.413.

Trying to explain the low Precision of the classification, we tested other classification methods (Random Forest, Logistic regression). However, since they didn't outperform the C4.5 (J48) classifier, we did not include these results in the current research document.

One possible explanation for that is that although we were expecting unhindered movement for priority signs, vehicles seem to decelerate at these locations for various reasons. Mainly there are interactions between vehicles in real-world traffic affecting individual trajectories corresponding to different traffic regulations

Methodologically also, the training process as conducted has the following weakness. As explained in 2.4, a single label is assigned uniformly to the samples that cross a certain class of junctions. That way, the classifier maps a speed profile to a label, no matter if at a traffic light location a vehicle stops (red light), decelerates (slow traffic due to previously red light) or just moves with slight modification on speed (green). Obviously, these cases result in quantitatively different speed profiles, assigned though under our current training the same label.

Similarly to the yield locations, there may be more than a single speed profile type that is observed at these locations. Perhaps the different speed profile classes should be assigned to different labels and the decision over the final label of the junctions should be done according to the mixture of different labels that are predicted for the same location.

Last, the feature vector as used by the selected classification method does not convey the linear ordering inherent in the temporal (or spatial) sampling and could explain why the decision tree did not perform as expected. Approaches that take advantage of the temporal structure such as LSTM or GRU could also be tested. The exploration of this line of observations is left for future research.

4 Conclusion

This paper proposed a method for classifying intersections according to traffic controls and based on the speed profiles of vehicles when passing the junction. We tested different combinations of features for the classifier and settings for the validation step. Best performance was achieved using a segmentation of the trajectories on the time domain in a temporal window starting at eight seconds before the junction's centroid until the center of the junction, sampled every second and using a buffer size of 50m. The classification shows high Recall for traffic lights, but due to the high rate of FP (yield signs predicted as traffic lights), the Precision and F-measure are relatively low. Next step of this research will be the exploration of different speed profile categories within the control categories and the classification of junctions according to the aggregated labels of the detected speed profile classes (a single location can then have a mixture of different labels corresponded to different speed profile classes) by using a classifier which takes into account the temporal order of the data used in the feature vector.

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