Towards regulation-aware navigation: a behavior-based mapping approach

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Abstract

In this paper we describe a framework for *regulation-aware* navigation. Such navigation presupposes maps with geo-referenced road regulations. By road regulations we mean, the set of the rules that defines which driving actions are allowed or not at a given location. These rules become operative most commonly with the known graphic form of the traffic signs seen alongside the roads. The motivation for including such information on the maps is the driving safety, which is endangered when regulations are violated. Three challenges are distinguished for the realization of regulation-aware navigation. Two refer to the recognition and mapping of the rules and the third to the classification of driver's predictive behaviour based on the geo-referenced local regulation context: 1) the inference of the road network regulations, 2) the mapping of regulation-compliant manoeuvres (which manoeuvres are allowed given the local regulatory context) and 3) the real-time recognition of driver's intent which is then classified as non-violating or violating given the valid rules. For the recognition of rules posed by regulatory signs we propose a method of analysis of vehicles' trajectories based on the detection of stop and turn manoeuvres. Hidden-Markov models are also proposed for the task of behaviour recognition, where at the observable layer we emphasize the role that samples from direction-indicator and brake sensors can play in the early recognition of the intended driving maneuvers.
Keywords: regulation-awareness, trajectory analysis, Hidden-Markov models, maneuver recognition, traffic-signs.

1 Introduction

The expanding use of navigation devices nowadays is due to the ease and convenience with which they support the drivers. A major prerequisite of their use are the up-to-date and accurate maps. For this reason much research focuses on how maps can be kept updated given the frequent changes, either temporal or permanent of the road network (temporal closures due to construction works or natural disasters, new roads, changes on segments of current roads, etc.). The research interest in that case lies basically on the extraction of the geometrical and topological features of the road network, with different methods having been proposed for automating the map construction process [3, 5]. The innovative element behind these map-inference methods is that they rely not on data taken with special survey equipment, a process that is time and cost expensive, but on crowdsourced GPS traces captured by everyday vehicles with simple GPS devices. So, using only spatiotemporal samples (longitude-latitude-time) from vehicles which operate as probes, both the geometry and the connectivity of the road segments can be acquired fast and at acceptable accuracy.

Under a broader view, a map could be seen not only as a compact representation of the space and the movement limitations that the road network imposes, but also as a description of the driving behaviour limitations that road regulations introduce. In this case, a map should denote not only the geometrical and topological features of the road network but it shall also *explicitly* display the local manoeuvre restrictions that regulations initiate (e.g. do not turn left, one-way road, do not go through the intersection, compulsory stop, etc.) and which are of major safety significance. Traffic navigation systems do contain this kind of information; however the problem is to keep it up-to-date as alterations of the traffic rules are made as often as the modifications of the other two features. Consequently, it emerges the need of finding a computational method for identifying the valid traffic-rule context so that its modifications can be discovered and renewed when maps are being updated. Furthermore, crowdsourcing this kind of information allows to also reveal typical behaviour of travellers, e.g. slowing down in a curve to a moderated velocity. This could be used as a recommendation in the long term run, leading to more adequate and situation adapted regulations.

This paper aims to explore how the automated map construction process and the navigation per se can benefit, if the regulation context is to be included to map representations. This is supported by harnessing GPS samples coupled with additional data derived through Can-Bus from in-car sensors with which today manufactured vehicles are equipped. As prospective data we mention namely the blinkers (direction indicators), the brake, the steering wheel angle, the speed, the acceleration, the gear indicator, the car yaw and the side vehicle sensors. We assert that maps that include the road rules can be the first step towards *regulation-aware* navigation. We envision maps that incorporate the expected driver's behaviour based on the local valid set of road rules, so that they can operate as classification boundaries for the observable driving behaviour. Inconsistencies between the expected behaviour and the predicted one indicate violation of road rules and by identifying such deviations, assistive actions can be triggered accordingly, such as warning alerts and verbal suggestions.

2 Motivation

Automotive safety is a topic of great interest for both drivers and automakers. Advance Driver Assistance Systems (ADAS) aim to assist drivers at the complex driving process by detecting pedestrians (PPSs), facilitating parking, lane departure and intersection crossing, recognizing traffic signs and by adapting the speed for collision avoidance, just to name a few. Recently, a trend is observed for enhancing the performance of such safety-oriented systems by fusing data from map and other sensor sources. For example Peker et al. [8] propose the fusion of map matching and traffic sign recognition for detecting traffic signs with higher likelihood. Satzoda et al. [9] show how a multimodal synergistic approach for automated driving analysis can be implemented by analysing data from different sources (CAN Bus, map and GPS devices) in a collaborative and complimentary manner. Lefèvre et al. [6] predict driver's intent at road intersections relying not solely on vehicle kinematics and dynamics but also on contextual information in the form of topological and geometrical characteristics of the intersections derived from maps. The performance in test cases of the proposed methods of the aforementioned studies shows improvement over the results of relative methods which count on single-source input data.

In the context of navigation, safety issues are limited in most of the cases to speed limit reminders and notifications for speed limit excess. For this reason, maps that include the local regulation framework could contribute in safety reinforcement. Adopting a data fusion approach for constructing such maps, data from different sources (GPS devices, CAN-Bus signals) could be fused for inferring the local rule context. Among the numerous rules that different regulatory signs set in operation, at the current research we consider a small subset of them, which is shown in Figure 1.

Figure 1: Set of road regulations that this study focuses on.

The geo-referenced regulatory signs can operate then as "guides" at the problem of classifying a driving maneuver as compliant or violating with regard to the locally valid regulation framework (Table 1). This means that each sign can be assigned to a set of "do-not" or "allowed-to-do" *expected* driving actions, so that the classification of the predictive behavior uses it as a reference point. For example, driving inside the "geo-fence" of a stop sign, the expected behavior is a stop maneuver. Predicting this maneuver from observable data with low likelihood (how probable is the observation sequence under the stop maneuver model?) it would recommend to classify the observed maneuver as rule-violating, given the expected behavior at that location is a stopping maneuver.

Table 1: Classification of observable driving behavior

		Predictive observable maneuver	
		$maneuver_i$	$maneuver_j$
Expected maneuver	$maneuver_i$	compliant	violating
	$maneuver_j$	violating	compliant

The problem of recognition, prediction and modeling of driver's behavior or intent has been addressed with many different techniques. Torkkola et al. [10] use Hidden Markov Models (HMMs) for modeling sensor sequence for maneuver classification, Oliver & Pentland [7] use Coupled HMMs (CHMMs), an extension of HMMs, to create models of seven different driver maneuvers and Aoude et al. [1] classify behavior at intersections using Support Vector Machines. Armand et al. [2] propose a method based on Gaussian Processes to learn and model the velocity profile (deceleration behavior) that the driver follows towards a stop intersection, so that *individuality* in driving behavior does not produce false predictions. Thus, we partition the problem of regulation-aware navigation in three sub-problems: 1) How given a location, can the current regulations be identified so that they get georeferenced and imported to the maps? 2) How can a geo-referenced road rule be "translated" to a set of permissible driving actions which stand for a location-based behaviour pattern? 3) How can driver's behaviour be classified as compliant or not in accordance to the local regulation context? These topics are discussed in the next sections.

3 Extraction of regulatory signs

3.1 Data sources

The regulatory signs that we consider in the current study (Figure 1) refer to intersection locations and define whether or not the entrance into a road segment through an intersection is allowable or compulsory (for the stop sign also under which conditions it is allowed) from an adjacent road segment. Suppose we have numerous GPS samples from vehicles that cross a given intersection, we can examine the trajectories of the vehicles resulting from the interpolation of the time-ordered spatial samples and deduce whether a rule from this set is applicable or not. Let's first examine the case of the compulsory signs. Given a sign indicating that drivers must turn left, we expect all the trajectories that depart from that road segment to turn left. In similar way we explore the trajectories for the compulsory right turn. The task then is to detect for each trajectory departing from that road segment if it turns left (right) or not. The detection of turning points usually relies on the plausible assumption that at such a point a vehicle reduces its speed and changes direction. Karagiorgou & Pfoser [5] for the task of intersection detection find clusters of turning points by identifying the latter based on experimentally determined thresholds for the speed and the change of direction (40km/h and 15° respectively). A similar assumption, that is, the heading direction of the vehicles change greatly (more than 45°) at intersections, is done in [11] for the same task (detection of intersections).

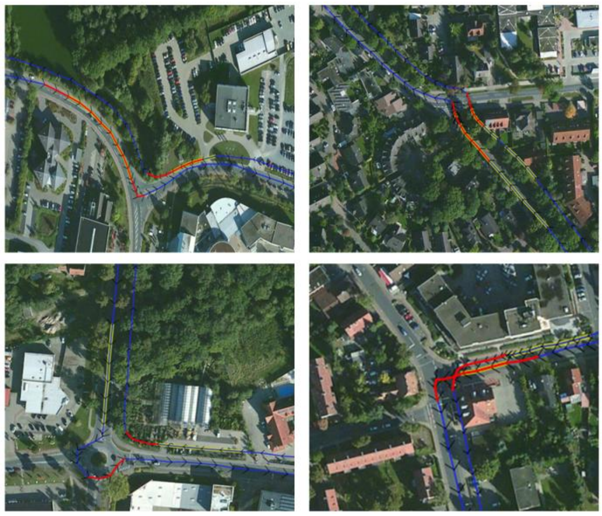
The problem with using these two criteria for asserting whether a point on a trajectory is a turning point, is that the reduction of speed is not a unique indicator for turning (a vehicle can be enforced to reduce its speed in an urban area for many different reasons) and if such an indication is coupled with noisy positioning (e.g. at stopping points noisy positioning due GPS error is common), we can mistakenly assign a noisy sample as a turning point. The same argument holds in the case of roads with big curvature where the vehicles move with low speed (and/or stop in random locations due to traffic incidents) and their direction changes greatly. Also, another issue on question is whether global speed and change of direction thresholds are adequate when the context of a problem, such that of intersections is highly variable from case to case. In order to infer a traffic sign reliably, it is required that it has to be hypothesized by many trajectories. To this end, clusters of similar trajectories (turn right, left, go straight on, stop), have to be found. In this context, false assignments to clusters or detecting wrong number of clusters considerably affect the accuracy of the result. For these reasons, we propose the additional integration of data derived from the blinker and brake sensors.

3.2 Trajectory analysis for sign recognition

The idea for using indications from blinker and brake sensors is quite intuitive: driving maneuvers are composed of a sequence of actions which shows great similarity among drivers, with small variance in regard to the context (similar sequence of actions for the same maneuver at different locations). For example, when someone wants to turn, he brakes for reducing vehicle's speed, indicates the intended direction (blinkers) and then turns. Figure 2 shows four instances of driving maneuvers (turn left, turn right, compulsory stop), where the spatiotemporal features of the blinkers and brake are presented. Consecutive samples from an activated sensor (red for blinkers and yellow for brake) form a trajectory which coincides with vehicle's trajectory (blue). As it can be seen in the figures, before a turn maneuver drivers brake and activate the blinkers. The order of these two actions can be reversed, which means that depending on the surrounding traffic, a driver might first brake, e.g. if other vehicles are stopped in a close distance from the intersection spot, or first indicate his intention to turn before he starts decreasing the speed, e.g. if there is no vehicle in front to enforce him to brake earlier from the intersection. It can also be the case, a short time interval to mediate after braking until direction signaling be activated (Figure 2, down left) because the speed has been already regulated for the intended maneuver and not further braking is needed. These observations motivate the usage of data from blinker and brake sensors, as their activation "constitutionally" accompanies such driving maneuvers. A two-step method is proposed for identifying potential valid road rules:

i. *Clustering of the trajectories:* we find clusters of similar trajectories, that is, trajectories that show the same maneuver pattern.
ii. *Analysis of the extracted clusters:* given a standard intersection of two roads, we examine the clusters extracted from the previous step similarly to [12] as follows. Entering the intersection from a road r_i:
   1. If only a right turn maneuver pattern has been identified (cluster of right turn), a compulsory *right turn* rule is valid.
   2. If only a left turn maneuver pattern has been identified, a compulsory *left turn* rule is valid.
   3. If it has not been detected any right *or* left turn pattern, a compulsory *drive through the intersection* rule is valid.
   4. If 1, 2 and 3 are not valid, and no turn-right cluster exists, then a *do not turn right* rule is valid.
   5. If 1, 2 and 3 are not valid, and no turn-left cluster exists, then a *do not turn left* rule is valid.
   6. If 1, 2 and 3 are not valid, and no go-through- the-intersection cluster exists, then a *do not drive intersection* rule is valid.
   7. If a stop maneuver pattern is detected, a compulsory stop rule is valid.

Figure 2: Instances from driving maneuvers (turn left- right, compulsory stop). Consecutive samples from activated blinker (red) and brake (yellow) sensors form trajectories which coincide with vehicle's spatial trajectory (blue).



Counting on crowdsourced naturalistic data for rule extraction relies on the assumption that drivers respect the rules, so the samples are expected to be in agreement with each local regulation context. Nevertheless, the dataset might still contain "violating" samples, either due to low attention or deliberate action. These samples need to be identified as such and their behavioural pattern not to be taken into account. Recognising anomalous behaviour patterns such as detour [4] due to loss of way or low attention level and reckless driving (aggressive acceleration, braking, left-right and u-turns) could explain individual samples or clusters composed by few members and consequently they could be excluded from the rule mining process.

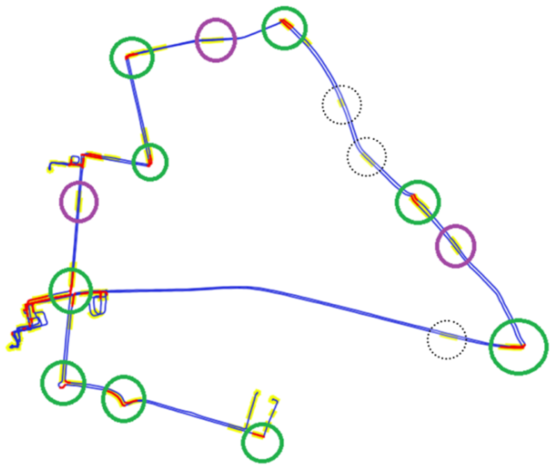
4 Driver behavior prediction for regulatory-aware navigation

Blinker and brake sensors were shown earlier to be good indicators of the maneuver pattern observed in trajectories. Due to their warning function, we believe that these features could also be used for the task of prediction of driver behavior. For this reason, for the task of classification of driving behavior according to the regulation-aware navigation framework, we propose a HMM-based maneuver recognition approach which uses data from these sources as "seen" variables at the observable layer. Under such an apporach, separate HMMs are trained for each driving maneuver. Approaching a regulatory sign, the sequence of observable variables is presented to each trained HMM. The maneuver model under which the observation sequence has the higher likelihood, recognizes the type of maneuver that a driver is performing. A manuever is classified as rule-compliant, when it coincines with the local expected maneuver. Warning messages are triggered elsewise. In addition, sensor data helps to indicate “interesting” situations, e.g. locations, where users brake often (after no regulation demand), so detection of violating patterns by different users could be an extra indication for a potential dangerous situation that could be prevented by modifying the current regulatory context.

5 Some examples

Although, our data collection is in progress, initial processing of the data shows promising results. In Figure 3 we observe how similar driving actions are spatially correlated. Different drivers apply alike sequences of actions in the same spatial context and by clustering the multi-dimensional samples, the repetitive location-based behaviors as posed by the valid regulation set can be revealed. It is also interesting the early usage of blinkers and brake before the actual maneuver takes place (60-120 m before beginning the change of direction at the turn maneuvers). For this reason, better predictive results are also expected on the task of driving behavior recognition.

Figure 3: Blue trajectories denote vehicle’s movement. Blinker and brake occurrences are shown in red and yellow respectively. With green and purple circles we denote *clusters* of similar *spatial behavior*. Black dotted cycles denote instances of the brake being observed at a single test case (not all the drivers brake at the same location, so this behavior cannot be considered as pattern). Sequences of blinker and brake followed by change of direction indicate turn pattern (green) and sequences of braking until stopping show stop maneuver (purple).



6 Conclusions

In this paper we described a general framework of regulation-aware navigation. We underlined as distinctive challenges the extraction of the local regulatory context, proposing a 2-step clustering-based method and the real-time prediction of the intended driving maneuvers using Hidden Markov Models. Our next step is going to be the testing of the proposed methods with real data and in real environment.

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