A Cognitive Assistant for Route Selection Using Knowledge Heuristics*

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ABSTRACT

Traditional route assistance systems such as Google Maps and Apple Maps enable drivers to find routes between two points optimised by distance or time of the route. However, such systems do not take into consideration habitual driving patterns or preferences of the driver. For example, a driver may usually avoid residential areas or prefer driving on motorways except when there is high traffic volume. Our work explores the potential of multi-modal data fusion to assist future connected vehicles in autonomous decision making. This will enable vehicles to offer an increased range of services to assist drivers, such as intelligent route selection. Motivated by this observation and due to the advancements in technology for both vehicles and infrastructure, in this extended abstract we present our work on a data-driven advisory platform that can reduce the cognitive burden on drivers in the driving environment. Specifically, we have implemented a set of technologies that can seamlessly harness the power of driver specific information and correlate this information with features of the road network such as static properties of the road itself (e.g. road type) or dynamic properties of the road network (e.g. traffic flow) so that drivers can be presented with alternative routes based on the perceived cognitive load of different road segments.

KEYWORDS

Cognitive Load Prediction, Knowledge Representation, Journey Planning

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1 INTRODUCTION

Given the rapid increase in urbanisation and a change in the mobility patterns of humans, traffic on our road networks is expanding at an exponential rate which adds to the cognitive burden of drivers[1, 7]. The problem is exacerbated by the fact that road users are drowning in information. This is due to a variety of reasons: (1) vehicles and their environments produce a lot of data. A recent study estimates that today's connected vehicles produce around 25GB of data for every hour of driving[6] - a vast amount of information for a driver to analyse. (2) people are evermore connected; the overwhelming amount of information, be it social information or work related information (e.g. calendar, email) and an *always-on* attitude makes people tense whilst they are on the road[1,2]; and last but not least, (3) with the advancement in technology, people are getting used to receiving contextual information such as places to visit relevant to their interests.

Motivated by the above observations, our work is focused around building a data-driven advisory platform to reduce the cognitive burden on drivers whilst they are on the road. Specifically, we have implemented a set of technologies that can seamlessly harness the power of driver specific information and correlate this information with features of the road network such as static properties of the road itself (e.g. road type) or dynamic properties of the road network (e.g. traffic flow) so that drivers can be presented with alternative routes based on the perceived cognitive load of different road segments. To realise this platform, we have brought together a set of research-grade tools: (1) a library to extract Open Street Map (OSM) data and efficiently create graph models over relevant features so that search algorithms can be executed with respect to the context of the problem; (2) a knowledge representation mechanism [2] to generate unified models using a multitude of data so that seamless and inter-operable information and knowledge integration is supported; (3) a library to support query interpretations in the given domain[3]; and (4) a big data based approach to efficiently compute the perceived cognitive load between two points.

We have discussed (1), (2) and (3) in our recent publication at the IEEE Vehicular Technology Conference which contains technical details of our approach [3]. In this extended abstract we will discuss how cognitive load prediction is augmented over our state-of-the-art system along with an evaluation utilising data collected from the Stuttgart region to demonstrate it's applicability in real-world situations.

2 EVALUATION APPROACH

In order to identify features of the road network that lead to an increase in cognitive workload for the driver, we utilise a dataset proposed by Schneegass *et. al* collected in the Stuttgart region in Germany[9]. This dataset consists of physiological data as well as ground truth labels for cognitive workload, labelled by participants

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[1] http://ibm.biz/sciencealert_feeling-busier
[2] http://ibm.biz/businessinsider_feel-busy
[3] https://github.com/ce-store/ce-store/wiki/Hudson-Summary

during a post experiment video rating session. For the purposes of our work, we utilise the ground truth labels from this dataset, however, it is plausible to gather data directly from the driver or vehicle itself, if the collection capability were available.

2.1 Road Segment Workload Weighting

Using the video rated ground truth labels, it is possible to identify specific road segments that lead to high, medium and low workload for each participant. Values in the `Rating_Videorating` column are normalised and binned according to pre-defined thresholds of > 0.75 for high workload, > 0.5 and <= 0.75 for medium workload and > 0.25 and <= 0.5 for low workload.

Given our previous work extracting static features of the road network from OSM [3], we apply similar techniques to extract and store OSM data for the Stuttgart region in a geospatially indexed MongoDB database [8] which enables rapid querying of the OSM data. We then query the MongoDB database for static road features surrounding the locations of high, medium and low workloads. Road feature weights can then be computed to infer how each road feature affects workload, based on the road features identified near to the locations of the observed workload. In our evaluation we used a simple approach to calculate the feature weights that correspond to different levels of workload—i.e. the number of road features is summed for each workload level and multiplied by a fixed weight of `10` for high workload, `5` for medium workload and `1` for low workload. Road feature weightings for participant 1 are shown below:


```
{"trunk_roads": 68, "trunk_link_roads": 52, "
    motorway_link_roads": 54, "unclassified_roads
    ": 10, "primary_link_roads": 1, "
    tertiary_roads": 60, "secondary_roads": 30, "
    tertiary_link_roads": 1, "residential_roads":
    108, "secondary_link_roads": 16, "
    primary_roads": 1, "motorways": 37}
{"severe_curvature": 91, "roundabouts": 20, "
    crossings": 118, "moderate_curvature": 125, "
    traffic_signals": 108, "high_curvature": 126,
    "low_curvature": 219, "traffic_calming": 1}
```


This shows that residential roads have a greater impact on workload for participant 1 than other roads, along with pedestrian crossings and road curvature.

2.2 Cognitive Workload Journey Planning

We construct a graph by extracting OSM nodes and ways for the Stuttgart region to provide the foundations for a journey planning capability. We then implement A* search [5], where the cost function for each edge (OSM way) is a function of distance to the end goal as well as cognitive load according to the workload weights obtained previously. This allows the journey planner to select the most appropriate route from a starting OSM node to a destination OSM node for each participant based on the cognitive workload weights for that participant. The journey planner is implemented as a Python Flask [4] application whereby the weights along with the start and end node are specified using a HTTP POST request at query time. In order to illustrate this, below we provide some examples using the journey planner to navigate from OSM node '1879217774' to OSM node '246645238' in the Stuttgart region. Setting all the cognitive load weights to 1 enables the journey planner to take the shortest path to the destination as shown by Figure 1.

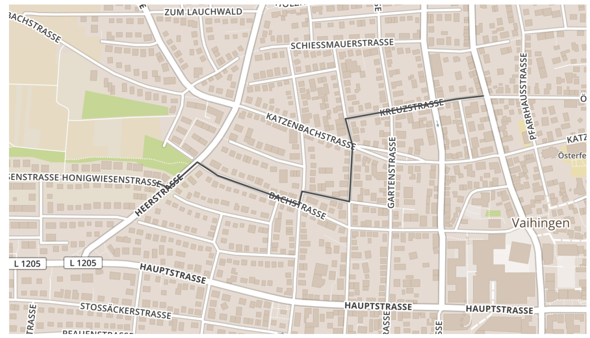

Figure 1: Shortest Path from Start Node to Destination Node

However, using the road segment weights for participant 1 as calculated above enables the journey planner to avoid residential roads as this exercises a greater workload on the driver as shown by Figure 2.

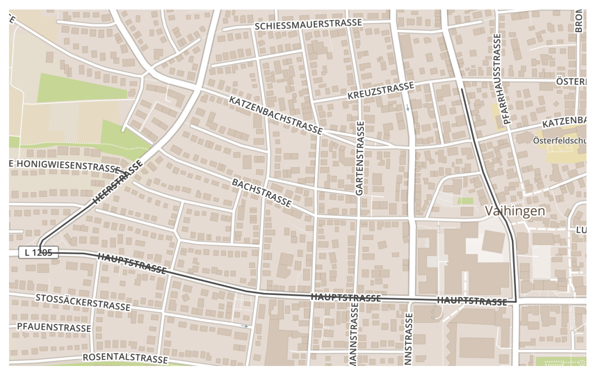

Figure 2: Path using Cognitive Load Weights for Participant 1

3 CONCLUSION

Through this extended abstract, we have discussed our technology platform to realise the vision of route selection optimised by cognitive workload. We have evaluated the platform using an open source data set on driving patterns from the Stuttgart region. Our demonstration shows how a multitude of data sources and driver preferences can be fused together in a seamless manner to predict the perceived cognitive load of a driver and offer a more personalised, intelligent service such as route selection. Our current research is focused on learning utility vs risk profiles of drivers and vehicles so that cognitive workload can be computed as a set of functions which can then be used to forecast the cognitive workload thresholds for a given driver, vehicle and the environment.

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