Defining input parameters of Fuzzy Inference Model for detecting Traffic congestions

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Summary

Fuzzy logic is shown to be a promising method for solving complex traffic problems and fulfilling traffic demands. Since traffic processes are characterized by subjectivity, ambiguity, uncertainty and imprecision, we suggest using fuzzy inference model for detecting traffic congestions at previously specified road segments. Moreover, we aim to investigate which traffic parameters are most suitable for detecting traffic congestions and to which degree the choice of these parameters influence the output interpretations. In our example, we use two combinations of input parameters - traffic flow/density and mean speed/occupancy.

KEYWORDS: Fuzzy Inference Model, Traffic congestion, Congestion parameters

1. Introduction

An increase in traffic results in congestion growth, but also more accidents and air pollution. Even though traffic congestion might be inevitable, there are ways to deal with this phenomenon. While many support the idea of improving transportation systems through building new roads or repairing aging infrastructures, others argue that the future of transportation lies not only in concrete and steel, but rather increased application of information technology. This approach enables elements within the transportation system (e.g. vehicles, roads, traffic lights, message signs, etc.) to become intelligent by embedding them with microchips and sensors and empowering them to communicate with each other through wireless technologies (Ezell, 2011). Moreover, traffic and transportation engineers emphasize the importance of implementing traffic guidance and control using the road resources effectively. These ideas evolve into the discipline known as Intelligent Transportation Systems (ITS) whose general aim is to fulfill increasing traffic demands and facilitate efficient utilizations of transport infrastructure.

Often, existing deterministic and stochastic models show to be non-effective in solving complex traffic problems and fulfilling traffic demands. This is mostly because dependencies between traffic variables are too complex or sometimes even vaguely defined. Additionally, dealing with ambiguity, uncertainty and vagueness in traffic events requires rather imprecise quantities and subjective notion of acceptability, as well as judgement in the calculation and interpretation of the results. Therefore, we suggest using fuzzy inference model for detecting traffic congestions at specific road segments or entire transportation networks. Moreover, we are interested to investigate which traffic parameters (e.g. traffic flow, velocity, density) are most suitable for detecting traffic congestions and to which degree the choice of these parameters influence the output interpretations. In our example, we use two combinations of input parameters (traffic flow/density and mean speed/occupancy) for our fuzzy inference model and discuss our findings.

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2. Fuzzy Logic Theory and Fuzzy Inference System (FIS)

Fuzzy logic theory was first introduced by professor Lotfi A. Zadeh (1965) as a mean of representing and manipulating data that was not precise, but rather fuzzy. Due to the fact that many traffic related problems are rather ambiguous, vague and characterized by subjectivity, one has to take into account that modelling these problems is also approximate and includes uncertainties regarding the accuracy and representation of the real conditions. With that in mind, one can approach fuzzy logic theory to recognize these vague occurrences and properly model traffic events, such as congestion.

Fuzzy inference system is the process of formulating the mapping from a given input to an output using fuzzy logic (Fullér and Zimmermann, 1993). The process itself involves several phases: defining and fuzzyfying input parameters, applying fuzzy rules and operators, applying an implication and an aggregation method, and defuzzification. The fuzzification of inputs refers to the necessity to define to which degree the input belongs to the appropriate fuzzy set. Fuzzy rules and operators are specified for projecting input variables onto an output space. The implication method consists of reshaping the resulting fuzzy set, while the aggregation method aggregates outputs of all rules into a single fuzzy set. At last, the defuzzification process determines the single value from the fuzzy set.

In this paper, we aim to emphasise the importance of properly defining input parameters. This is a challenging task and involves both knowledge and experience in the specific field (Klir and Yuan, 1995).

3. Definition of parameters

Fuzzy inference model input parameters are at the same time measures that explain traffic congestion events. Based on the traffic flow theory, there are three traffic flow characteristics which are most suitable for describing congestion phenomena – density (k), flow (q) and mean speed (v) (Wardrop, 1952). Additionally, there exists a unique relation between these variables known as the fundamental relation of traffic flow theory (Equation 1). This relation provides a close bond between the three quantities, since knowing two of them allows calculating the third.

$$q=k*v \tag{1}$$

Density allows us to get an idea of how crowded a certain section of a road is. It is typically expressed as the number of vehicles per kilometer (or mile). Daganzo (1997) also defines density as the total time spent by all the vehicles in a measurement area, divided by the total size of that area. Whereas density is a spatial measure, flow can be considered as a temporal measurement. *Flow* is defined as the number of vehicles per hour (hourly rate). Edie (1965) defines the flow as the total distance travelled by all the vehicles in the measurement region and divided by the area of that region. Third variable - *mean speed* is expressed in kilometers (or miles) per hour. In other words, it is calculated as the total distance travelled by all the vehicles in the measurement region, divided by the total time spent in this region (Edie, 1965; Daganzo, 1997). Sometimes, the fourth variable – occupancy might be used for doing some analysis. Occupancy is a temporal measure and refers to the fraction of time the measurement location was occupied by a vehicle (Coifman, 2001).

4. Data and fuzzy inference model

We use the Mobile Century data (Herrera et al. 2010) collected on February 8th, 2008 at the Interstate 880, as part of a joint UC Berkeley - Nokia project. The dataset includes cell phone GPS data, Inductive Loop Detector (ILD) data obtained through the Freeway Performance Measurement System (PeMS), and travel time data obtained through vehicle re-identification using high-resolution video data. For our analyses, we use the ILD data only.

ILD data is collected at 27 locations and consists of flow and occupancy data for each lane, at every 30 second interval. We use a subset of the dataset with the time interval between 6pm and 9pm. The highway stretch (its total length is 18km) is divided into six segments. The segments are not of the same length, but rather follow the spatial distribution of detector loops. The segment ends before the highway entrance, or starts after an exit (depending on where the station is placed). Additionally, we observe congested traffic in each of the four lanes individually and calculate the average level of congestion at each segment during the time interval between 6pm and 9pm.

We first use traffic flow and density as the input parameters for the fuzzy inference model (density is derived from the occupancy, assuming homogeneous traffic and same vehicle lengths). We fuzzyfy the inputs with linguistic variables, which are further treated with previously specified fuzzy rules. As a result, we get detected levels of congestion at the segmented highway sections, in each lane separately. We repeat the same procedure using the second combination of input variables – occupancy and mean speed (mean speed is calculated from flow and density information using Equation 1).

5. First results and Outlook

Very first results show us that detected levels of congestion notably differ among each other. In Figure 1(a), we observe near congestion-to-congestion levels in all four lanes (south – east to north – west direction). Stable traffic is detected only in lane 1, segment 1 and lane 4, segment 6. Figure 1(b) shows different pattern. Detected traffic conditions very from stable to unstable in all lanes, with a few near-to-congestion segments.

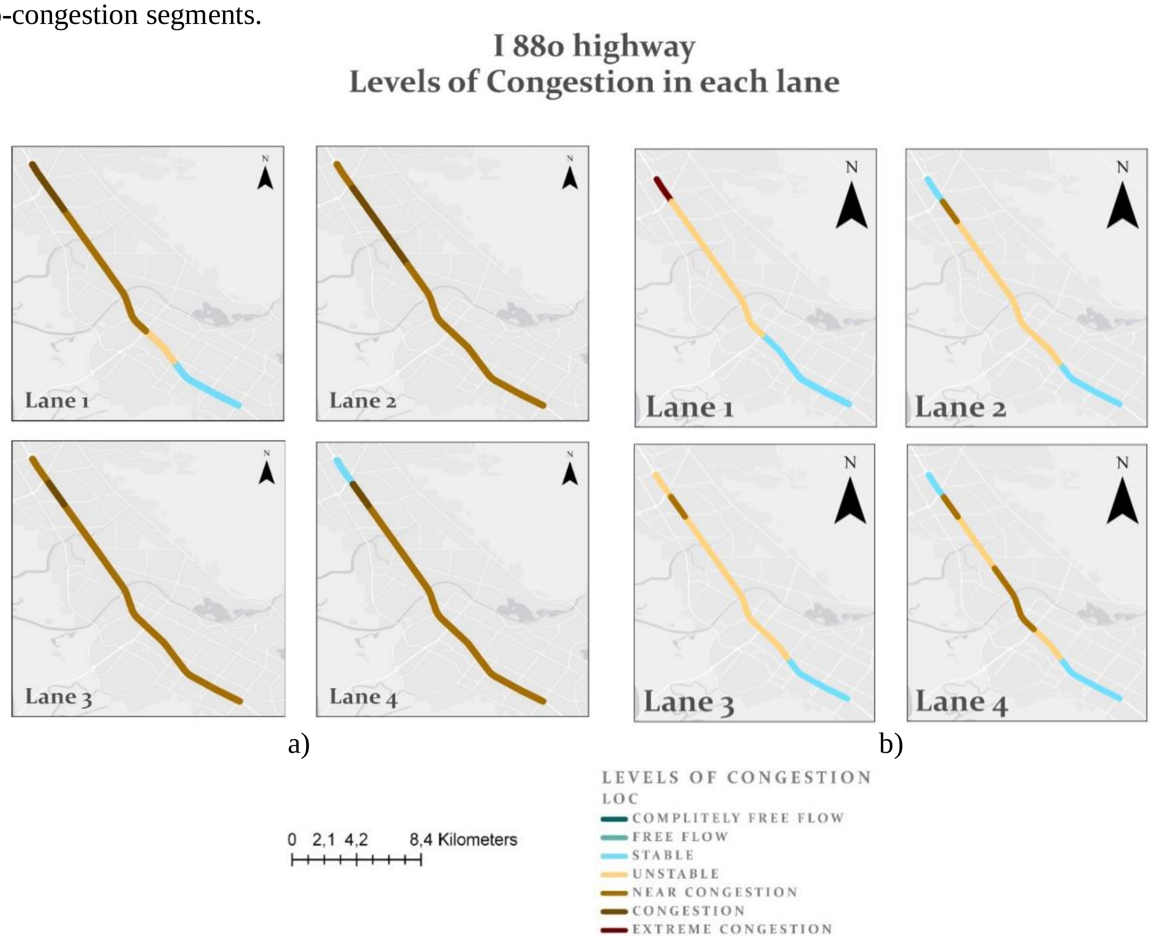

Figure 1 Levels of congestion (LOC) detected between 6pm and 9pm on February 8th, 2008, stretch of highway I 880 – Northbound direction, in all four lanes. Image a) shows the LOC using traffic flow and density as input parameters, while the image b) resulted from an occupancy and mean speed parameter combination.

While these outputs result from rather short observation period (6pm – 9pm) and sparse study area (18km highway stretch), we could not but wonder what those would be if we were to use complete dataset. In addition, we are curious to see results in case if we extend the number of input parameters for our fuzzy model beyond variables that constitute fundamental relation of the traffic flow theory (adding variables such as weather conditions, time of the day, day of the week, etc.). These and accompanied questions we plan to investigate in our further research.

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Biographies

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