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Fuzzy similarities for road environment-type detection by a connected vehicle from traffic sign probabilistic data

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Abstract

The road environment recognition using embedded technologies has been researched intensively recently. Several papers deal with the detection of the urban road environment-type (RET), such as downtown, residential area, and business/industrial area. These RETs can characterize the road environment around an ego-car. A RET detection approach taking into account relevant traffic signs (TSs) that are visible from the ego-car – along its route – was also proposed. It was assumed that the TS data, namely the type and the location of each detected TS along the route, was made available for the purpose by an on-board TS recognition system (TSR). The TS data is constantly updated, aggregated and evaluated in a multi-scale manner by a RET detection system, so one can produce a probability series of occurrence of each TS type with respect to each of the considered urban RETs. In the present paper, we develop a heuristic for dynamic RET detection using fuzzy similarities on a special graph. We also propose the generic process of this approach, which will be the subject of further development and testing.

Keywords: Smart mobility, smart road vehicles, road environment-type detection, fuzzy set theory, reactive systems, machine learning.

1. Introduction

'Connected', *'cooperative'*, *'smart'*, *'intelligent'* and *'autonomous'* are labels that appear these days in numerous scientific publications and in many commercial advertisements in conjunction with up-to-date road vehicles. It comes as no surprise to anyone working in this application field as the road vehicles characterised with one or more of the above features are foci of intensive research and development (R&D) effort throughout the world.

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Safety and regulatory compliance applications are based on knowledge of the vehicle environment; therefore, the detection of the environment plays a key role in this area. These applications have an impact on the Advanced Driver Assistance Systems (ADAS), and they necessitate novel ADAS functions. Some of these functions concern environment detection, and while some monitor the actual driving situation of the vehicle. Clearly, situational awareness is an essential task for both present and future ADAS [12] [8].

As part of Hungarian-Moroccan scientific cooperation, a research project entitled "Detecting the urban environment and driving a smart road vehicle - with a little help from friends" was launched. In the frame of this project, we look into some interesting aspects of the field [7].

Previous works [6] [9] present several approaches for the detection of the type of road environment, such as city centers, residential and industrial/commercial areas, based on signaling data collected by an on-board signal recognition system. Data on the type and location of traffic signs (TSs) are evaluated at several levels, that is, on short, medium and longer portions of the road. There are many other methods targeting similar recognition tasks. Several solutions were published for roadside detection, objects on the road, traffic lights and road signs [14][11][5].

In the present paper, we develop a new approach for urban road environment-type (RET) detection using fuzzy similarity calculus. Our method develops an occurrence-probabilities learning matrix of the TSs, and crossroad (CR) categories along roads section. Then this matrix is transformed into a set of fuzzy subsets. The RET identification is elaborated by a simple calculation of similarity between the detection vector provided by the ego-vehicle and the fuzzy sets previously established.

The remainder of the paper is organized as follows. The relevant objectives and definitions of the data used by the detection process are presented in Section 2. The proposed approach and the exploration process for the detection of RETs, as well as the theoretical construction of the fuzzy similarity are described in Section 3. In Section 4, we present the architecture of the prototype system. The paper will be concluded in Section 5.

2. Background

The future connected cars will be equipped with computer systems of substantial computing capabilities. On one hand, these systems will ensure storage, access to, management, analysis and processing of large volumes of data, some of which will have been produced on-board by the cameras and various sensors. These data volumes could and will support a range of purposes and will be processed and evaluated by the on-board computer system. On the other hand, the connected cars will able to harness hardware and software resources hosted at other – either static, or mobile – sites so that they can exploit the extremely high performances available at these sites. In this manner, advanced data analyses can be carried out for real-time decision making (e.g., for dynamic route planning) for the connected car. It will also be important for the data communication system to be efficient and flexible enough to keep the costs – associated with data with limited lifetime/validity/relevance (e.g., data regarding the road traffic surrounding the ego-car) – low. At a first sight, the data collected on a road vehicle may seem less important than that data produced and managed within a company. Yet, firstly, there could be hundreds or even thousands of cars/trucks within a commercial fleet making the operation and management of the fleet fairly complex and significant in an economic sense, secondly, a car/truck – be it standalone, or a member of a fleet – can be thought of as a more or less independent system: it generates, stores and manages its own data internally (i.e., on-board), which is then might be sent to a public or private data warehouse for storage and analysis. As data – in particular data generated on-board – becomes more and more essential and ubiquitous, the importance of choosing of a trustable partner for its handling and management should not be underestimated. Automotive connectivity will not work in any useable way, unless the data collection, data transfer, the access to and the analysis of data is devised properly. Furthermore, these activities must be underpinned and supported by suitable information and communication technologies. These need to be scalable to provide for the development of new intelligent vehicular features and functions. Big Data approach for detecting, processing and evaluating complex vehicular events. All collected vehicular data must be filtered and processed to detect events of significance. Complex Event Processing (CEP) is an event-processing concept for identifying significant events in a mass of events. The complex events are discovered via inference, analysis and correlation of elementary events [3]. The CEP system can exhibit capabilities like: the potential to produce results as soon as the input event stream is available, the ability to carry out calculations (e.g. time difference between two events interest), the ability to provide real-time, or near real-time alerts/notifications, particularly if complex event-patterns have been detected, the ability to link and correlate data coming from heterogeneous data sources, and to discover intrinsic patterns, and lastly, the possibility of guaranteeing high throughput and low processing time.

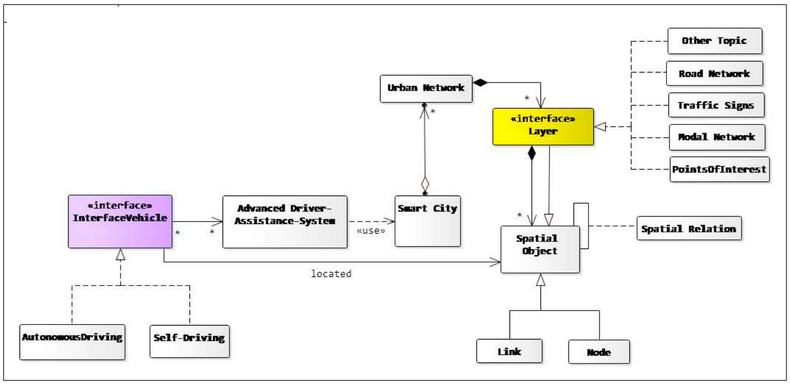

Fig. 1. Moving Ego-vehicle Model.

The above diagram (Fig.1) mainly specifies the location of a mobile object (vehicle, autonomous vehicle) in the network. Its location via a device allows it to be located on a spatial object (link or intersection). A city is composed of several urban networks (depending on mode). An urban network consists of several layers (geographic theme). Spatial objects interact by spatial relationships (topological or otherwise). A vehicle has a driver assistance system (or navigation for pedestrians). Figs. 2 - 4 summarize the themes that encapsulate a city, the mobile browser is presumed to detect objects nearby. These objects belong to a geographical theme, etc.

Fig. 2. (a) Gis layers ; (b) Traffic Signs.

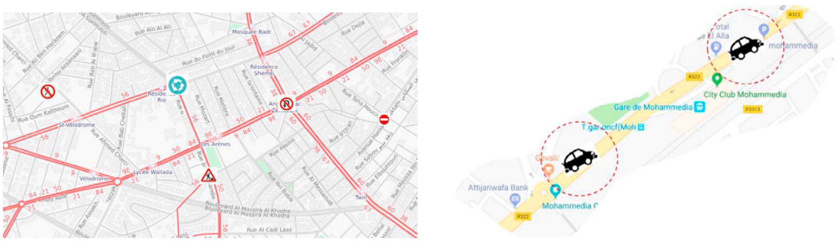

Fig. 3. (a) Traffic Signs on Roads layer (Casablanca center from openstreetmap) ; (b) Navigation of the ego-vehicle aware of its environment.

3. Fuzzy similariy analytics RET-detection system

The theory of fuzzy sets has been over several decades, a great utility for solving complex problems. The uncertain nature of the data and the fuzziness of human decision have been very well modeled by this theory. In this section,

Fig. 4. Ego-vehicle with detection device and sensors.

we recall the elements needed to understand the remainder of the paper. Essentially, we recall here the definitions of fuzzy and similarity concepts [2], [4], [17], [15], [16]. In this section, we present also some elements of notation used.

It is known that the fuzzy modeling generalizes that given by the probabilities. Thus the theoretical constraints of the theory of probabilities [18] are exceeded.

3.1. Definitions

3.1.1. Fuzzy sets

If X is a collection of objects denoted generically by x, then a fuzzy set $\widetilde{A}$ in X is a set of oredred pairs [18]

$$\widetilde{A} = \{x, \mu_{\widetilde{A}}(x) | x \in X\} \tag{1}$$

$\mu_{\widetilde{A}}(x)$ is called the memership-function or grade (also degree of compatibility or degree of truth) of x in $\widetilde{A}$ that maps X to the membershio space M (When M $=\{0, 1\}$, $\widetilde{A}$ is crisp set and $\mu_{\widetilde{A}}(x)$ is identical to the characteristic function of nonfuzzy set).

The (crisp) set of elements that belong to the fuzzy set $\widetilde{A}$ at least to the degree α is called the $\alpha - level$ set :

$$A_\alpha = \{x \in X \mid \mu_{\widetilde{A}}(x) \geq \alpha\} \tag{2}$$

$A'_\alpha = \{x \in X \mid \mu_{\widetilde{A}}(x) > \alpha\}$ is called 'strong $\alpha - level$ set' or 'strong $\alpha - cut$'. Throughout this paper, the following notations is used. $\mathbb{R}^+ = [0, \infty); X = \{x_1, x_2, ..., x_n\}$ is the universal set; $\mathcal{F}(X)$ is the class of all fuzzy sets of X; $\mu_A(x_i) : X \longrightarrow [0, 1]$ is the membership function of $A \in \mathcal{F}(X)$; $A^c \in \mathcal{F}$ is the complement of $A \in \mathcal{F}$.

3.1.2. Similarity between fuzzy sets

We define two similarity measures $S : \mathcal{F}^2 \longrightarrow \mathbb{R}^+$ between fuzzy sets A and B as follows [4]. The first one is as follows:

$$S(A, B) = \left\{ \sum_{i=1}^{n} \left[\frac{\mu_A(x_i) \otimes \mu_B(x_i)}{\mu_A(x_i) \oplus \mu_B(x_i)} \right] \right\} \diagup n \tag{3}$$

where $a \otimes b$ and $a \oplus b$ denote the minimum and maximum values of a and b, respectively. In order to avoid the denominator being zero, we set $\frac{0}{0} = 1$ in the usage of (3). The second similarity measure is as follows:

$$S(A, B) = \frac{\sum_{i=1}^{n} [1 - |\mu_A(x_i) - \mu_B(x_i)|]}{n} \tag{4}$$

In the remainder of the paper, we will make use of the similarity defined by the relation (3).

3.2. Notation

Hereinafter, we describe some useful notations for the rest of the paper.

$E_i = \{spatial\ object\ of\ layer\ (i)\} = \left\{e_j^{m,i} \,|\, j = 1..n\right\}$ which defines a layer.

The set of all layers : $E = \cup_i E_i$

$\vartheta_i\,(m,\varepsilon) = \{o \in E_i \,|\delta\,(m,o) \leq \varepsilon \bigvee \mathcal{L}\,(m,o) \vdash true\}$ all the objects of the layer E_i which are at a distance ϵ from the mobile (i). $\mathcal{L}\,(m,o)$ defines a spatial predicate between the mobile m and the object o.

$\mathbb{C} = Road\ Environment - Type\ \ (RET) = \{\sigma_i \,|i = 1..m\}$

Example: $\mathbb{C} = \{downtown,\ residential\ area,\ business\,|industrial\ \ \ area\ ,\ \ldots\}$

3.3. Fuzzy data

In data mining, data is represented in a matrix, with individuals being represented as rows and variables as columns, with each individual being associated exactly one value for each variable. In the following, we consider the case where the variables are discrete and the individuals present a distribution rather than a single value for each variable. This can be a probability distribution, when the data is uncertain, a frequency distribution, or a fuzzy set. In the table below is synthesized the frequency occurrence matrix of TSs and CR categories according to types of roads. It is build from the occurrence histograms given in [9], [10].

Table 1. The probability of occurrence of TS's and CR's – along a 50 m path-length –in the three urban RET's considered from [9][10].

RET / TS	σ_1 Downtown	σ_2 Residential	σ_3 Industrial/Commercial
γ_1	22%	3%	4%
γ_2	18%	2,5%	1,7%
γ_3	7%	8%	5,5%
γ_4	2%	4%	2%
γ_5	28%	32%	20%
γ_6	13%	8%	1,5%
γ_7	1%	0,5%	0,1%
γ_8	0,1%	0,2%	0,2%
γ_9	5%	2%	4%

Where:

$E_{TS} = \{\gamma_1, \gamma_2, \gamma_3, \gamma_4\}$

$E_{CR} = \{\gamma_5, \gamma_6, \gamma_7, \gamma_8, \gamma_9\}$

$\mathbb{C} = \{\sigma_1, \sigma_2, \sigma_3\}$

3.4. Detection by fuzzy similarity

The process of building fuzzy sets is very simple. Each column, corresponding to a RET (see Table 1), is associated with a fuzzy set. The probability of occurrence of TS and CR types is interpreted as a membership degree to a fuzzy set. Hereafter, we illustrate this process by infered fuzzy sets:

- Infered Fuzzy sets

  $(D)\,\sigma_1 = \left\{{}^{\gamma_1}/0.22, {}^{\gamma_2}/0.18, {}^{\gamma_3}/0.07, {}^{\gamma_4}/0.02, {}^{\gamma_5}/0.28, {}^{\gamma_6}/0.13, {}^{\gamma_7}/0.01, {}^{\gamma_8}/0.001, {}^{\gamma_9}/0.05\right\}$

  $(R)\,\sigma_2 = \left\{{}^{\gamma_1}/0.03, {}^{\gamma_2}/0.025, {}^{\gamma_3}/0.08, {}^{\gamma_4}/0.04, {}^{\gamma_5}/0.32, {}^{\gamma_6}/0.08, {}^{\gamma_7}/0.005, {}^{\gamma_8}/0.002, {}^{\gamma_9}/0.02\right\}$

  $(IC)\,\sigma_3 = \left\{{}^{\gamma_1}/0.04, {}^{\gamma_2}/0.017, {}^{\gamma_3}/0.055, {}^{\gamma_4}/0.02, {}^{\gamma_5}/0.20, {}^{\gamma_6}/0.015, {}^{\gamma_7}/0.001, {}^{\gamma_8}/0.002, {}^{\gamma_9}/0.04\right\}$

Thus, each RET's is considered as a fuzzy set and each CR or TS belongs to a fuzzy set through a membership degree. Based on this, the RET detection process is defined as follows. The ego-vehicle collects the TSs and CRs over a given distance, and generates a detection vector consisting of these signs. This detection vector is a "crisp" set. Subsequently, a similarity computation with the RETs defined as fuzzy sets makes it possible to select the right type, according to the criterion of maximization of the similarity. This process is summarized below:
Recall that the learning phase of the occurrence matrix of probabilities is necessary and predetermines the recognition process.

- RET-detection system similarity based algorithm

  1. *Learning step (pre-processing)*
  2. *Fuzzy matrix building* $TS \times RET$
  3. *RET fuzzy sets building* $\mathbb{C}$
  4. *Calculation of the similarity between the detection vector* Θ *and the fuzzy sets RET* $\mathbb{C}$
  5. *Select the most similar RET to the vector detection* Θ

- Illustration of the detection process
  Fuzzy calculation of similarity with each fuzzy set.
  Case 1
  $S(\sigma_1, \{\gamma_1/1, \gamma_2/1, \gamma_3/1\}) = (0.22 + 0.18 + 0.07)/(1 + 1 + 1 + 0.02 + 0.28 + 0.13 + 0.001 + 0.05) = 0,47/3,49 = 0,134$
  $S(\sigma_2, \{\gamma_1/1, \gamma_2/1, \gamma_3/1\}) = (0.03+0.025+0.08)/(1+1+1+0.04+0.32+0.08+0.005+0.002+0.02) = 0,135/3,467 = 0,038$ $S(\sigma_3, \{\gamma_1/1, \gamma_2/1, \gamma_3/1\}) = (0.04 + 0.017 + 0.055)/(1 + 1 + 1 + 0.02 + 0.2 + 0.015 + 0.001 + 0.002 + 0.04) = 0,112/3,278 = 0,034$
  Case 2
  $S(\sigma_1, \{\gamma_2/1, \gamma_3/1, \gamma_4/1\}) = (0.18+0.07+0.02)/(0.22+1+1+1+0.28+0.13+0.01+0.001+0.05) = 0.27/3.691 = 0.073$
  $S(\sigma_2, \{\gamma_2/1, \gamma_3/1, \gamma_4/1\} (0.025 + 0.08 + 0.04)/(0.03 + 1 + 1 + 1 + 0.32 + 0.08 + 0.005 + 0.002 + 0.02) = 0.145/3,457 = 0,041$ $S(\sigma_3, \{\gamma_2/1, \gamma_3/1, \gamma_4/1\}) = (0.017 + 0.055 + 0.02)/(0.04 + 1 + 1 + 1 + 0.2 + 0.015 + 0.001 + 0.002 + 0.04) = 0.092/3.298 = 0,027$
  Case 3
  $S(\sigma_1, \{\gamma_4/1, \gamma_5/1\}) = (0.02 + 0.28)/(0.22 + 0.18 + 0.07 + 1 + 1 + 0.13 + 0.01 + 0.001 + 0.05) = 0.3/2.661 = 0.112$
  $S(\sigma_2, \{\gamma_4/1, \gamma_5/1\} = (0.04 + 0.32)/(0.03 + 0.025 + 0.08 + 1 + 1 + 0.08 + 0.005 + 0.002 + 0.02) = 0.36/2.242 = 0.161$
  $S(\sigma_3, \{\gamma_4/1, \gamma_5/1\}) = (0.02+0.20)/(0.04+0.017+0.055+1+1+0.015+0.001+0.002+0.04) = 0.22/2.17 = 0.101$
  Case 4
  $S(\sigma_1, \{\gamma_3/1, \gamma_9/1\}) = (0.07 + 0.05)/(0.22 + 0.18 + 1 + 0.02 + 0.28 + 0.13 + 0.01 + 0.001 + 1) = 0.12/2.841 = 0.042$
  $S(\sigma_2, \{\gamma_3/1, \gamma_9/1\} = (0.08 + 0.02)/(0.03 + 0.025 + 1 + 0.04 + 0.32 + 0.08 + 0.005 + 0.002 + 1) = 0.1/2.502 = 0.0399$
  $S(\sigma_3, \{\gamma_3/1, \gamma_9/1\}) = (0.055+0.04)/(0.04+0.017+1+0.02+0.2+0.015+0.001+0.002+1) = 0.095/2.295 = 0.041$
  Case 5
  $S(\sigma_1, \{\gamma_1/1, \gamma_5/1\}) = (0.22 + 0.28)/(1 + 0.18 + 0.07 + 0.02 + 1 + 0.13 + 0.01 + 0.001 + 0.05) = 0.5/2.461 = 0.203$
  $S(\sigma_2, \{\gamma_1/1, \gamma_5/1\} = (0.03 + 0.32)/(1 + 0.025 + 0.08 + 0.04 + 1 + 0.08 + 0.005 + 0.002 + 0.02) = 0.35/2.252 = 0.155$
  $S(\sigma_3, \{\gamma_1/1, \gamma_5/1\}) = (0.04+0.20)/(1+0.017+0.055+0.02+1+0.015+0.001+0.002+0.04) = 0.24/2.15 = 0.111$

The data presented in Table 2 described above, consolidate the calculations made previously. Identified RETs agree exactly with the expected results from the studied urban environments.

The connected vehicle has the power to communicate with other vehicles, such as with the road infrastructure (see Fig.5). It can also be equipped with sensors to receive the information sent by the signal panels equipped with infrared transmitters. The car can recognize TSs. Other sensors and intelligent methods are used to recognize objects in the neigberhood of a vehicle. Vehicles equipped with a software system, roam the roads of the city to build the connection matrix between the TSs and the RETs. This correspondence matrix is used to construct probabilities of occurrence of TSs and CRs according RET. The probability matrix generates the RET fuzzy sets. Finally, once the ego-vehicle

Table 2. Illustration of the RET detection process

Case	Detected sequence (50m)	$(D)\,\sigma_1$	$(R)\,\sigma_2$	$(IC)\,\sigma_3$	RET
1	γ_1 γ_2 γ_2	0,134	0,038	0,034	D>R>I
2	γ_2 γ_3 30 γ_4	0.073	0,041	0,027	D>R>I
3	30 γ_4 γ_5	0.112	0.161	0.101	R>D>I
4	γ_3 γ_9	0.042	0.0399	0.041	D>I>R
5	γ_1 γ_5	0.203	0.155	0.111	D>R>I

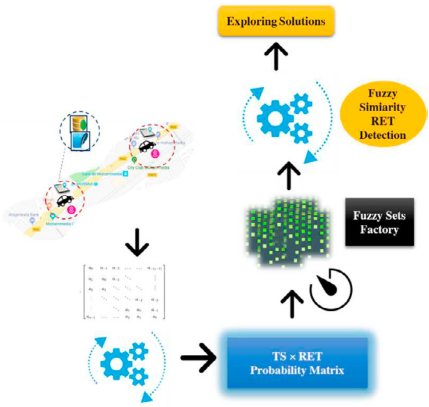

Fig. 5. Exploration process mining architecture.

gives a detection vector composed of TSs and CRs to the fuzzy similarity recognition system, then the identification procedure provides the appropriate RET.

4. Exploration and system archiecture

A distributed architecture is highly required to deal with efficient data processing in a constrained environment like urban roads. To realize our proposed approach with a scalable and reusable system, we adopt the microservices approach in which each part of the detection process is integrated into independent service deployed as needed [13]. In addition, we implement the microservices with reactive principles (Responsive, Resilient, Elastic and Message Driven) to offer great possibilities whereby each component is individually developed, released, deployed, scaled, updated and removed. The RET detection system is composed with small microservices such as : a spatial database engine, on-board ego-vehicle RET detection system, fuzzy similarities learning system, etc. Those micoservices use asynchronous messaging to communicate with other similar services.

The proposed system operates over a cloud environment and integrates several underlying technologies: sensing, data interpretation, communications, information integration, and control to build a large, efficient and real-time tool. The architecture consists of a set of components, organized into five categories: a proxy server, API gateway, message broker, services, and customers. The server proxy serves to establish secure connections with all clients; moreover, all message exchanges with the system must comply with an API gateway. The API Gateway serves as the single entry point for all clients. It is responsible for authenticating users, routing requests to the appropriate service, generating events for services to consume, as well as load balancing. For inter-service communication, we use a message broker designed as a partitionbased publish/subscribe distributed message queue. The services that make up the inter-system were built in isolation continuously tested, deployed and integrated using container technology (Docker) [1].

5. Conclusion

In this work, we have developed a new approach for RET detection. The probabilities data developed by learning on the urban transport network have made it possible to transform these stochastic data into fuzzy sets. Herein, only TSs and CR types were utilized in the RET recognition, however, other types of data collected by the ego-vehicle may also be used (e.g., number of lanes, lane-width).

The heuristic based in the calculation of fuzzy similarity yielded convincing results. The use of fuzzy set theory opens up promising prospects for better targeting the problem of RET detection. We plan to create fuzzy algebraic structures to generalize our approach and produce intelligent and effective learning methods to RET detection. Technical considerations of microservices are also challenges to ensure scalable reactive operation and ensure acceptable real-time deployment that can support RET data collection. Field experimentation is a big challenge, too. The software components planned for this experiment are presently being finalized. The other task is to compare our approach with other known approaches and methods.

In our view, the results presented in this work are convincing. The example given herein is based on real TS and CR data. As a further step, we plan to carry out data collection and RET detection in different cities.

Acknowledgements

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