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A novel self-organizing fuzzy rule-based system for modelling traffic flow behaviour

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ABSTRACT

The study and development of transportation systems have been a focus of attention in recent years, with many research efforts directed in particular at modelling traffic behaviour from both macroscopic and microscopic points of views. Although many statistical regression models of road traffic relationships have been formulated, they have proven to be unsuitable due to multiple and ill-defined traffic characteristics. Alternative methods such as neural networks have thus been sought but, despite some promising results, their design remains problematic and implementation is equally difficult. Another salient issue is that the opaqueness of trained networks prevents understanding the underlying models. Hybrid neuro-fuzzy rule-based systems, which combine the complementary capabilities of both neural networks and fuzzy logic, constitute a more promising technique for modelling traffic flow. This paper describes the application of a specific class of neuro-fuzzy system known as the *Pseudo Outer-Product Fuzzy-Neural Network* using *Truth-Value-Restriction* method (POPFNN-TVR) for modelling traffic behaviour. This approach has been shown to perform better on such problems than similar architectures. The results obtained highlight the capability of POPFNN-TVR in fuzzy knowledge extraction for modelling inter-lane relationships in a highway traffic stream, as well as in generalizing from sample data, as compared to traditional feed-forward neural networks using back-propagation learning. The model thus obtained automatically can be understood, analysed, and readily applied for transportation planning.

1. Introduction

Much attention has been paid in recent years to the study and development of intelligent transportation systems and research efforts have been directed in particular at modelling traffic behaviour from both macroscopic and microscopic point of views (Hoogendoorn & Bovy, 2001). Although many statistical regression models have been formulated, they have turned out to be unsuitable due to their inability to address the multiplicity and complexity of road traffic characteristics and relationships. Alternative methods such as probabilistic approaches (Boel & Mihaylova, 2004; Chowdhury, Santen, & Schadschneider, 2000; Hoogendoorn & Bovy, 2001) and neural networks (Castro-Neto, Jeong, Jeong, & Hana, 2009; Dougherty & Kirby, 1994; Shen, 2006) have thus been sought, the results of which are comparable or better than that obtained using mathematical models, especially in areas such as driver behaviour prediction, road pavement maintenance, vehicle detection and classification, congestion detection, and traffic control analysis (Boel & Mihaylova, 2004; Castro-Neto et al., 2009; Dougherty & Kirby, 1994). Despite some promising results, the difficulties in the design and implementation of neural networks remain unresolved – especially with regard to ill-defined problem characteristics – and the opaqueness of the trained systems prevents understanding of the underlying models, which is a major drawback in traffic-related applications (Castro-Neto et al., 2009; Shen, 2006). A viable solution is thus to adopt instead a knowledge-based approach that consists of automatically extracting from data a set of expert rules to model the problem and subsequently applying these rules independently (Hayashi, Nomura, Yamasaki, & Wakami, 1992). In the case of traffic flow and driver behaviour modelling, such rules can represent those characteristics that are invaluable to traffic engineers. The model thus obtained becomes useful in developing highway and transportation plans, performing economics analysis, evaluating the service quality of transport facilities, and selecting and implementing traffic control measures (Chow, Choy, & Lee, 2006; Shen, 2006; Wen, 2008). In addition, this model provides traffic engineers with the basis for a viable platform for transportation planning and simulation.

The synergistic combination of neural networks and fuzzy logic is seen as a very promising technique for automatically deriving from experimental data an approximate yet robust rule-based model. The hybrid technique blends the strengths of both fuzzy and neural systems while alleviating their respective weaknesses, namely lack of training for fuzzy systems and the opaqueness of the neural networks. This paper describes a novel approach to the analysis and modelling of traffic flow using a specific class of self-organizing fuzzy rule-based system known as the *Pseudo*

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Outer-Product Fuzzy-Neural Network using the *Truth-Value-Restriction* method (POPFNN-TVR). As the original POPFNN-TVR, developed in-house (Zhou & Quek, 1996), implements a fixed-label architecture that is not suitable for traffic modelling, it was modified into a generic architecture that can accommodate multiple labels. The system was then trained and employed specifically for inter-lane traffic and driving behaviour modelling, as elaborated in the following sections, as well as for short-term traffic flow prediction (Quek, Pasquier, & Lim, 2006). The results obtained indicate that the modelling ability of POPFNN-TVR is comparable to and often better than of feed-forward neural networks using conventional back-propagation learning (FFBP) (Rumelhart, Hinton, & Williams, 1986). It also performs better on this problem that similar architectures (Ang, Quek, & Pasquier, 2003; Quek & Zhou, 1999), that have been thoroughly benchmarked against other methods. More importantly, POPFNN-TVR offers the added advantage over FFBP and other pure connectionist approaches of providing a set of explicit knowledge rules extracted from the training data. The fuzzy rules are identified to be representative of the problem being modelled and are invaluable in that they can be understood, analysed, and applied directly without further training or complex implementation.

2. Traffic flow analysis

This section summarizes fundamental traffic flow characteristics and associated analytical techniques, the knowledge of which is essential in the planning, design, and operation of transportation systems.

2.1. Macroscopic and microscopic analysis

A transportation system can be viewed as consisting of many moving particles that interact with one another as well as with the environment. Traffic flow analysis can be performed using either *microscopic* parameters, which relate to the behaviour of individual vehicles in the traffic stream with respect to each other, or *macroscopic* parameters, which describe the traffic stream as a whole. Microscopic parameters include characteristics such as *spacing* and *headway*, which refer to the distance between the front bumpers of successive vehicles in a traffic stream and the time delay between successive vehicles as they pass a particular road location, respectively. Both the spacing and headway of individual vehicles vary over a range of values that is generally based on the speed of the traffic stream. Therefore, in aggregate, microscopic parameters are related to the macroscopic flow parameters: *speed*, *volume*, and *density*.

On the one hand, microscopic analysis may be selected for moderate size systems where the number of vehicles is relatively small and there is a need to study their individual behaviour. On the other hand, macroscopic analysis may be selected for higher density, larger scale systems, for which a study of the global behaviour of groups of vehicles is sufficient. Macroscopic analysis is chosen in this project since our main objective is to model a highway section as a whole. The following sub-sections describe macroscopic flow parameters and models, as well as the data used in the project and the data collection method employed.

2.1.1. Speed

Speed is an important measure of the quality of traffic service provided to motorists. As commonly defined, speed is the rate of motion in distance per unit of time expressed in kilometres per hour (km/h) (Institute of Transportation Engineers, 1994). Normally, the average speed for the traffic stream as a whole is computed. In practice, speed can be expressed in two forms, namely the *Time Mean Speed* U_t and *Space Mean Speed* U_s given in Eqs. (1) and (2), respectively, where d is the distance travelled (km), n the number of travel time points observed, and t_i the travel time of the ith vehicle to traverse the given highway section

$$U_t = \sum_{i=1}^{n} \frac{(d/t_i)}{n} \tag{1}$$

$$U_s = \frac{nd}{\sum_{i=1}^{n} t_i} \tag{2}$$

Time mean speed is defined as the average speed of all vehicles passing a point on the highway over a specified time period, and can be measured using radar guns or similar devices. Space mean speed is defined as the average speed of all vehicles occupying a given highway section over some specified time period, and can be obtained typically using two inductance loops placed at short distance apart. It is frequently used in macroscopic models to describe the average speed of a traffic stream. Time mean speed and space mean speed are related as shown in Eq. (3), where σ is the variance of sample speeds

$$U_s = U_t - \frac{\sigma^2}{U_t} \tag{3}$$

2.1.2. Volume

Traffic volume or flow provides the means to quantify traffic and is defined as the number of vehicles that pass a particular location or a given lane of the highway during a specified time interval. It is expressed in vehicles per unit of time, and is sometimes defined on a per lane basis. Volume must not be confused with *rate of flow*, which represents the number of vehicles passing a location during a time interval less than 1 h, but expressed as an equivalent hourly rate. Volume of a given stretch of road can be recorded daily, hourly or sub-hourly. Even though traffic volume is useful for highway planning, it is not sufficient for designing operational facilities, because such a measure can only capture "peak-hour" information. Failure to take into account the short-term peak volume that occurs at sub-hourly intervals may lead to severe congestion when such conditions arise, thus a recording interval of 15 min is usually recommended (Institute of Transportation Engineers, 1994). In this project, a shorter time interval of 5 min was employed, as a substantial amount of data is required to train the system for short-term traffic forecasting.

2.1.3. Density

Traffic density is defined as the number of vehicles occupying a given length of highway or lane, and is generally expressed in vehicles per kilometres or vehicles per kilometres per lane. Density is considered as the most important among the three traffic stream parameters as it better gives an indication of traffic flow quality. Traffic density is directly related to traffic demand and it gives a measure of the distance between successive vehicles, thus reflecting their mobility based on the driver's psychological comfort. However, density is relatively difficult to measure directly and is usually derived from speed and volume parameters using Eq. (4), where K is the density (veh/km) and V the volume or flow (veh/h)

$$V = UK \tag{4}$$

2.2. Traffic stream relationships and models

Having introduced the principal macroscopic parameters of traffic streams, it is now appropriate to discuss the relationships among volume, speed, and density under uninterrupted flow conditions, the general form of which is illustrated in Fig. 1. It can be