Computer-Aided Civil and Infrastructure Engineering **13** (1998) 315–327

Traffic Prediction and Management via RBF Neural Nets and Semantic Control

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Abstract: *The objective of this work has been to develop layers of control and optimization modules for the purpose of urban traffic management. We utilize the semantic control paradigm to model both the macrolevel (traffic control) and the microlevel (vehicle path planning and steering control). A semantic controller consists of three modules for identification, goal selection, and adaptation, respectively. This hierarchical structure has been used successfully at the Center for Optimization and Semantic Control to solve complex, nonlinear, and time-varying problems. In our previous work we have used a judicious combination of artificial intelligence, optimization, and control systems.*

The focus of this paper is the identifier module, which performs "system identification," i.e., determines the road network congestion level. Traffic flow can be characterized as a nonlinear stochastic process where linear prediction models such as linear regression are not suitable. However, neural network techniques may provide an effective tool for data-based modeling and system identification. The radial basis function neural network (RBFNN) is an attractive tool for nonlinear time-series modeling and traffic-flow prediction. The goal selector module that finds the shortest path is also discussed in some detail.

A model of the highway system, based on historical data provided by Missouri Highway and Transportation Department (MoHTD), has been developed. The prediction and planning system is evaluated using the traffic-flow data from nine sensors located on the highway in the St. Louis metropolitan area.

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1 INTRODUCTION

The emergence of the various thrusts of Intelligent Transportation Systems (ITS)[1,15] presents numerous new theoretical and practical challenges; many of these deal with the modeling, prediction, cause-and-effect relationships, analysis, optimization, and control of an overall transportation system. In view of these, an advanced traffic management system (ATMS) will require a dynamic traffic model that can operate in real time and reliably predict traffic congestion. In general, the solution methodologies available for this problem can be grouped into five categories[1,15]: computer simulation, mathematical programming, optimal control, artificial intelligence, and intelligent control. Our methodology, one of intelligent/hybrid control, utilizes algorithms and tools from all the preceding approaches. Such hybrid systems for ATMS attempt to cope with the nonlinear and stochastic nature of traffic flow and incidents.

There are two approaches to a general prediction problem: explanatory and time series. *Explanatory forecasting* evaluates a cause-and-effect relationship between inputs to the system and its outputs. Usually, the inputs and outputs can be expressed as equations. On the other hand, *time-series forecasting* treats a system as a black box. The system is neither "fully" understood nor explicitly represented; therefore, the causes and effects at the output are not clearly explained. It relies on the discovery of strongly empirical regularities in the observation of the system. Traffic-flow forecasting can be viewed as a time-series prediction problem: Given a sequence $x(1), x(2), \ldots, x(N)$, predict the continuation $x(N+1), x(N+2), x(N+3), \ldots$. In the past three decades, several methods have been applied to traffic-flow prediction problems. Among these are the Kalman and adaptive filtering methods, as well as the Box-Jenkins method. They typically provide a one-step ahead prediction. The radial basis function neural network (RBFNN) has been proposed by different authors,[7,29] and it is an attractive tool for time-series prediction and system identification problem. Our goal here is to design a system identifier via RBFNN for every sensor station in the St. Louis area. Each system identifier uses the its own past traffic-flow data and other sensors' past traffic flow as input. The output of the system is the predicted traffic flow.

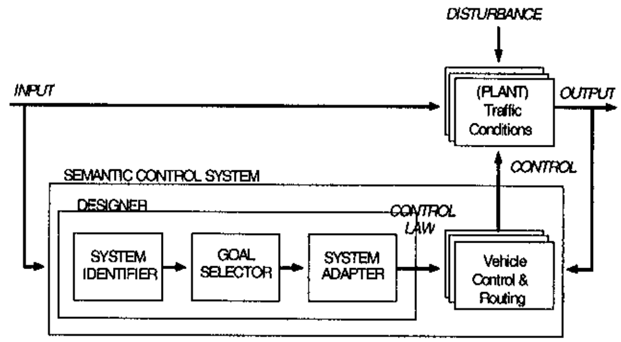

Fig. 1. A semantic control system consists of a system identifier, a goal selector, a control system adapter, and one or more control systems/laws.

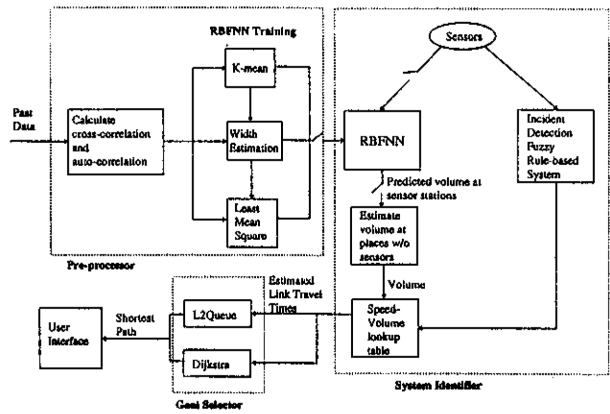

Fig. 2. Functional block diagram of the identifier and the goal selector modules.

1.1 Traffic management via semantic control

In this approach, utilizing the semantic control paradigm, we implement a hybrid prediction/routing/control system to model both the macro level (traffic control) and the micro level (in-vehicle path planning and steering control). A semantic controller consists of three modules for identification, goal selection, and adaptation, respectively. This hierarchical structure has been used successfully at the Center for Optimization and Semantic Control to solve complex, nonlinear, and time-varying problems.[3,16,24–26,34,36] A semantic controller (Figure 1) consists of

Identifier: Processes traffic data and interprets the available information for travel times and incidents.

Goal Selector: Generates and evaluates candidate paths and provides a traveler advisory.

Adapter: Implements vehicle steering control laws and provides driver's support.

A functional block diagram of our methodology is depicted in Figure 2; the system consists of three main parts: preprocessor, system identifier, and goal selector.

The preprocessor consists of codes for calculation of correlation coefficients and the radial basis function neural network (RBFNN) training algorithm. RBFNNs are trained to predict traffic volumes at nine sensor stations located along the major highways in the St. Louis area. As a part of the training algorithm, the auto-correlation coefficient and the cross-correlation coefficient between sensors are used to select inputs to the RBFNN for each sensor. After the input data have been selected, the K-means algorithm, width estimation, and least-mean-square algorithm are performed to complete the RBFNN training. The system identifier consists of an incident detection rule–based system, a volume estimator for nodes and/or links without sensors, and a speed-volume lookup table for speed estimation.

The goal selector handles traffic routing for maximum use of available road network capacity; the goal selector consists of two submodules, one for traffic management in signaled