MODELING OF LANE CHANGING DECISIONS OF DRIVERS FOR HETEROGENEOUS TRAFFIC OPERATION USING ADAPTIVE NEURO-FUZZY INTERFACE SYSTEM (ANFIS)

Sudipta Sarkar
Graduate Student, Department of Civil Engineering
University of Calgary, Canada
email: sarkars@ucalgary.ca

Dr. Md Shamsul Hoque
Associate Professor, Department of Civil Engineering,
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
email: shoque@ce.buet.ac.bd

Dr Richard Tay
Professor, Department of Civil Engineering,
University of Calgary, Canada
email: rtay@ucalgary.ca

Abstract

Lane-changing behavior models are important components of microscopic traffic simulation tools. Particularly, heterogeneity of traffic can significantly affect lane-changing behavior. The objective of this paper is to propose a framework for modeling the lane-changing behavior in a heterogeneous traffic scenario. The proposed model is built using the Adaptive Neuro-Fuzzy Interface System (ANFIS). Various membership functions of lane changing parameters are documented. Assignment of membership values for each class is done such that the obtained output gives a realistic measure of the likely outcome of different factor combinations to reflect driver decision to move laterally. Using a series of input-output data set, the model constructs a fuzzy inference system (FIS) whose membership function parameters are tuned (adjusted) using a combination of least squares method and a back propagation algorithm. This model could be used as an embedded tool for traffic simulation software, particularly to mimic lane changing behavior utilizing local data.

Background

Optimizing the transportation network is an important issue facing many cities in developing countries. Traffic congestion on urban roads is forcing city authorities to look at innovative transportation solutions. New road construction is no longer seen as the only solution due to financial constraints, lack of space and environmental impacts. Transportation engineering is continually changing with an increasing emphasis on applying computers and advanced technology in order to provide solutions that maximize the capacity of transportation networks. Traffic simulation model permits the evaluation of complex driver/vehicle/network interactions that cannot be adequately quantified using analytical techniques. For example, lane-changing behavior can more easily modeled using microscopic traffic simulation tools since the presence of road users, including non motorized traffic, can significantly affect lane-changing behavior. This paper presents a driver's lane-changing decision making model that has a generalized flexible structure and is applicable in all situations, including presence of non-motorized vehicles.

Traffic Heterogeneity

The traffic movement in Bangladesh and in many other developing countries is more complex than in most western countries due to the heterogeneous characteristics of the traffic stream using the same right of way. The stream includes slow pushcarts at one extreme and the fast moving passenger cars at the other, with many intermediate types of vehicles depicting a wide variation in static and dynamic characteristics. In such mixed traffic operation, no single vehicle type dominates the traffic stream.

Another distinguishing feature of the traffic under study is driving behavior, especially the lack of lane discipline. Under mixed traffic condition, road users often do not use lanes in the proper manner. Furthermore, lane markings on pavements along the road and near approaches are often not clear or missing entirely. If they exist, drivers rarely conform to them. Due to this lack of lane-discipline, lane-based analysis of traffic flow used in most western countries will not work well (Hoque, 1994).

Most existing driving behavior models do not have the capability to accommodate these special types of lane-changing behavior and hence the associated microscopic simulation tools are somehow not applicable in the analysis of mixed traffic environments. Thus, there is a need to develop more realistic lane-changing decision models that can capture the complexity of the lane-changing process in presence of non standard motorized vehicles.

Conceptual Development

In traffic modeling, driver maneuvers are usually characterized by various theories including macroscopic stream models, car following rules, queuing theories, gap acceptance and rejection considerations and merging rules. The choice of the adopted theories depends on the detail of the model. In heterogeneous traffic, it is imperative to verify if the characteristics of such traffic can adequately be described by the existing approaches. It also important to identify any explicit differences or phenomena which differentiate such streams from the more homogenous ones and to see how such differences could be included in the modeling approaches. Specific characteristics of heterogeneous traffic will differ with locality and prevailing traffic conditions, and many of them are known to influence the overall traffic performance. Common examples include non-lane based travel, abnormal queuing behavior exhibited by bicycles and motorcycles, the tendency for competing vehicles to initiate some contact leading to unpredictable driving patterns and random stopping of some vehicle types at undesignated areas to drop and pick passengers.

It is normally assumed that all vehicle movements occur within the confines of a single lane but this is not always so. Vehicles often use two lanes simultaneously either during lane changing maneuvers or even during normal travel. In the first instance, the non-lane based travel is temporal and lasts only during the lane change maneuver whereas in the second instance, it may take longer time. Although it has been recognized in many newer models (Minderhound, 1999; Van Aerde et al, 1996; Hoogendoom, 1999) that the lane changing process ultimately affects the flows on a vehicle's present and target lanes, there is hardly any detailed consideration given to prolonged simultaneous usage of two lanes. As observed by Gunay (1998), this latter case is more prevalent in traffic streams containing high percentages of non-standard vehicles which are common in many parts of the world.

The essence of the lane-changing behavior is a decision-making process. If the driver of the following vehicle in this lane is not satisfied with the current driving state, he/she will initiate a lane-change. Whether the adjacent lane can offer secure and comfortable interval is an important factor influencing the lane-changing behavior.

Since this judgment is based on the driver's knowledge and experience, and thus highly subjective, the fuzzy logic method is an approximate reasoning form to adopt in modeling. For example, Wang & Liu (2005) used a fuzzy approach to evaluate the safety and the comfort effects of relative speed and the relative distance. Fuzzy language variable like dangerous, small, medium, and big were used to represent input used to triangulate membership function.

Majority of this type of research, however, is based on fairly homogenous motorized traffic stream. The presence of other non-motorized slow vehicles could easily change the scenario. Therefore, conceptually and practically, a purely rule based fuzzy logic is not the appropriate modeling method. In this research, the Adaptive Neuro Fuzzy Interface System (ANFIS) will be used to model the driver's decision to lane change in heterogeneous traffic.

In the literature, a driver is a special object in simulation and is commonly referred to as an autonomous agent (Ni, 2006). It is autonomous because it acts on its own. It is driven by goals and is able to adapt to the changing environment. It is intelligent because it is able to reason or use the current context as a key to find solutions from its knowledge base and past experience. Thinking in an object-oriented (O-O) paradigm, relevant driver properties will include aggressiveness, alertness, perception-reaction time, preferences (lane and speed), etc. Driver goals can be expressed as a combination of the following constraints: origin and destination, safety and security, travel time, and other costs. Driver methods involve a complicated reasoning process to determine driving control strategies such as acceleration, deceleration, and steering based on the current context.

As an intelligent agent, a driver is able to (a) respond in a timely fashion to changes in the environment, (b) exercises control over his/her own actions, (c) pursue a goal by which to drive his/her actions, (d) communicate with other agents, and (e) change his/her behavior based on previous experience. These aspects of human intelligence can be modeled by artificial intelligence methods such as ANFIS. In solving complex, non-linear, and dynamic problems such as vehicle control, past research has shown that AI appeared to be more efficient than conventional deterministic mathematic approach.

ANFIS Model Structure and Learning Algorithm

ANFIS can be applied to any system for which the collection of input-output data is known. It is not necessarily to have a pre-determined model structure based on the characteristics of variables in system. There are some modeling situations in which it is difficult to discern the pattern of data and to determine the membership functions. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen to tailor the membership functions to the input-output data in order to account for these types of variations in the data values. This is where neuro-adaptive learning techniques can be used. The basic idea behind these neuro-adaptive learning techniques is very simple. These techniques provide a method for the fuzzy modeling procedure to learn information about a data set and to compute the membership function parameters that best allow the associated fuzzy inference system to track the given input-output data.

An adaptive FIS usually consists of two distinct modifiable parts: the antecedent part and consequent part. These two parts can be adapted by different optimization methods, one of which is the hybrid learning procedure combining gradient descent and least squares estimator. The antecedent part or If-part contains nonlinear parameters of membership functions that can take many different forms (Gaussian, triangular, trapezoidal, etc.). Membership function can be any function with range of [0, 1] used to represent their knowledge. Gradient decent method is used to adjust the nonlinear parameters. The consequent part or Then-part contains linear output parameters, which can be tuned with a least squares estimator. A network-type structure similar to that of a neural network can be used to interpret the input/output map. It maps inputs through input membership functions and associated parameters and outputs through membership functions and associated parameters.

The parameters associated with the membership functions will change through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input-output data for a given set of parameters. Once the gradient vector is obtained, an optimization routine can be applied to adjust the parameters to minimize some error measure (usually defined by the sum of the squared difference between actual and desired outputs). In this study, ANFIS uses a combination of least squares estimation and back propagation for membership function parameter estimation.

The learning algorithm for ANFIS is a hybrid algorithm which is a combination between gradient descent and least-squares method. More specifically, in the forward pass of the hybrid learning algorithm, node outputs go forward and the consequent parameters are identified by the least-squares method. In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descendent. Table 1 summarizes the activities in each pass. The consequent parameters are optimal under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster since it reduced the search space dimensions of the original pure back propagation method.

Table 1: Hybrid Learning Procedure for ANFIS

	Forward pass	Backward pass
Premise	Fixed	Gradient descent
Consequent	Least-squares	Fixed
Signals	Node outputs	Error signals

Lane Changing Model Structure

The first step in developing a lane changing decision model is to classify lane changing type (e.g. avoidance of obstruction, directional lane change, overtaking action, changing for shorter queue length, changing due to loading and unloading, random lane change, etc) and the respective exogenous factors (e.g. distance to critical point, available time, number of lanes to target lane, desired speed, actual speed, speed of forward vehicle, distance to present queue, difference in queue length, etc). Membership functions are then constructed based on their logical or experimental relationships for each exogenous factor (see Figure 1).

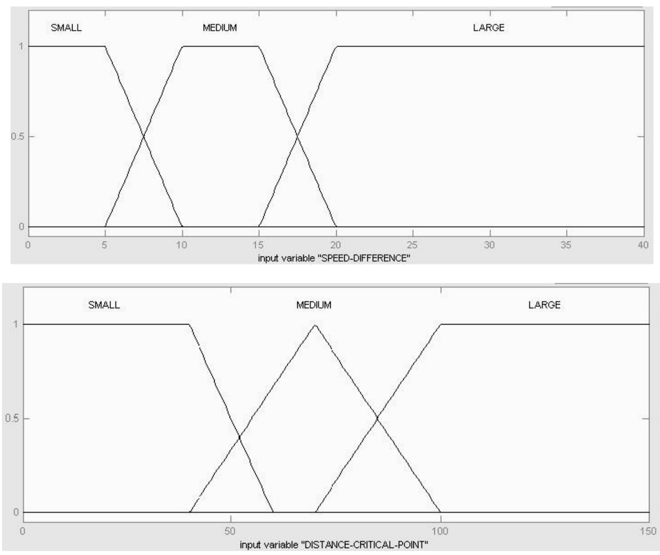

Figure 1: Fuzzy Membership Functions for the Different Parameters.

The second part, commonly referred as fuzzy inference, specifies the rules governing the whole process by combining two or more of the parameters. The aim is to infer what would happen to the component of the system governed by the rules when two or more of the parameters are combined. Rules can be defined for some or all possible combination of factors including the intermediary situations when the parameters are medium or high (see Figure 2). For an ANFIS model (see Figure 3 and Figure 4), different rules cannot share the same output membership function. The number of output membership functions must be equal to the number of rules.

Data Requirement and Model Validation

For training and checking of ANFIS model, a large set of data for input and output variables is required. Data could be collected using driving simulator, verbalization technique and any other sensor based mechanism. Data collection methodologies of this behavior model are varied and reported in (Sarkar, 2006).

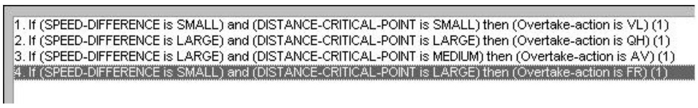

Figure 2: Rule Associated with ANFIS model Structure for Overtaking Action

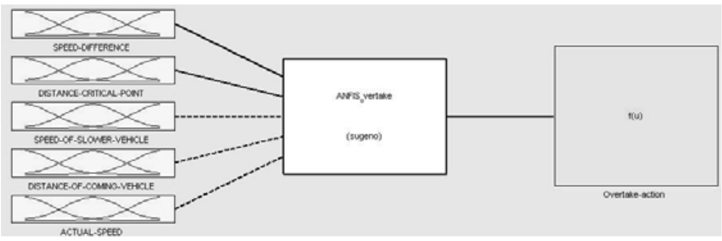

Figure 3: Model Structure for Overtaking Action using MATLAB®

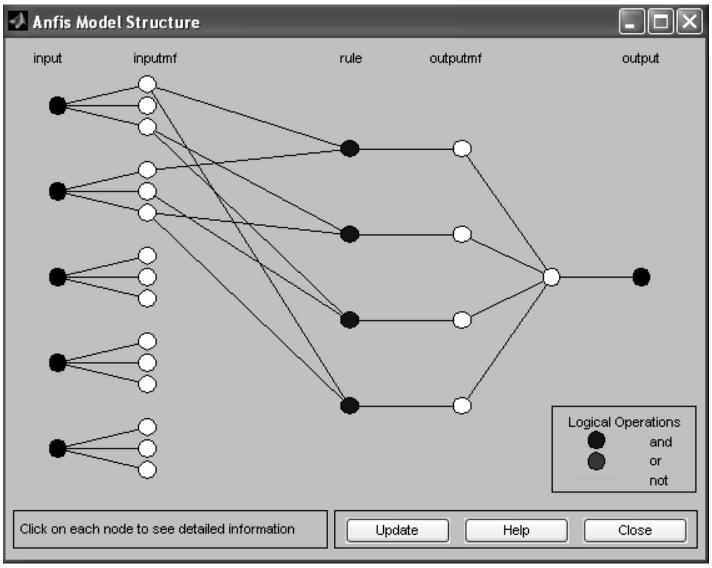

Figure 4: Model Structure using MATLAB ® for ANFIS for Overtaking Action

The training data is a required to train the ANFIS model. Each row of data file is a desired input-output pair of the target system to be modeled. Each row starts with an input vector (difference in speed, distance to critical point, time available, speed of slower vehicle etc) and is followed by an output value (decision values of lane change). This decision value could be expressed in linguistic variables such as Very Low (VL), Low (LW), Fair (FR), Average (AV), High (HG), Quite High (QH) and Very High (VH) with corresponding numeric parameters. Output functions quantify driver's decision for lane change. Input/output data in a form that is usable by ANFIS for training has been collected. Then ANFIS is used to train the FIS model to emulate the training data presented to it by modifying the membership function parameters according to a chosen error criterion. In general, this type of modeling works well if the training data presented to ANFIS for training (estimating) membership function parameters is fully representative of the features of the data that the trained FIS is intended to model. This is not always the case, however. In some cases, data is collected using noisy measurements, and the training data cannot be representative of all the features of the data that will be presented to the model. This is where model validation comes into play.

Model validation is the process by which the input vectors from input/output data sets on which the FIS was not trained, are presented to the trained FIS model, to see how well the FIS model predicts the corresponding data set output values. This is accomplished with the ANFIS Editor GUI using the so-called testing data set, and its use is described in a subsection that follows. This other type of validation data set is referred to as the checking data set and this set is used to control the potential for the model overfitting the data. When checking data is presented to ANFIS as well as training data, the FIS model is selected to have parameters associated with the minimum checking data model error.

One problem with model validation for models constructed using adaptive techniques is selecting a data set that is both representative of the data the trained model is intended to emulate, yet sufficiently distinct from the training data set so as not to render the validation process trivial. This problem could be overcame using large amount of data, hopefully this data contains all the necessary representative features, so the process of selecting a data set for checking or testing purposes is made easier.

The basic idea behind using a checking data set for model validation is that after a certain point in the training, the model begins to over-fit the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that over-fitting begins, and then the model error for the checking data suddenly increases (see Figure 5).

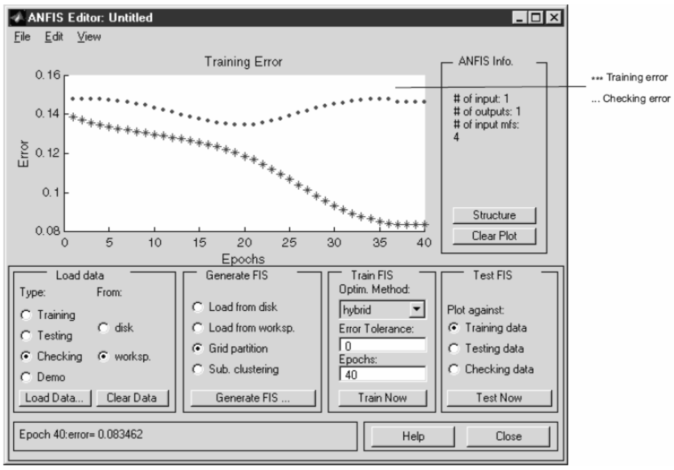

Figure 5: Plot of Training and Checking Error using MATLAB®

If the checking error decreases up to a certain point in the training and then it increases, then this is the point where the model starts to over-fit. ANFIS will choose the model parameters associated with the minimum checking error (just prior to this jump point). After certain amount of training, the membership functions would have changed and following modified membership functions are created (see Figure 6).

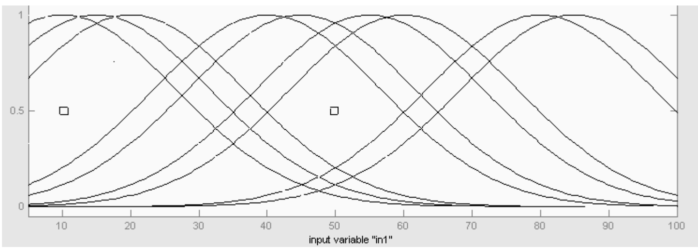

Figure 6: Modified Membership Functions (cont.)

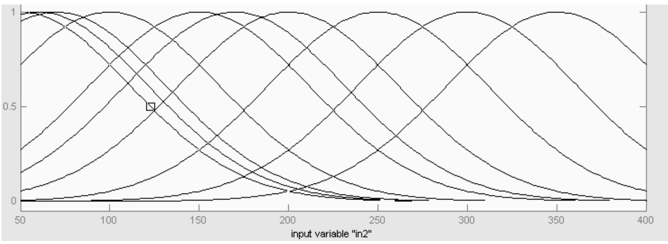

Figure 6: Modified Membership Functions

Conclusion and Future Research

The main contribution of this research is to develop a new lane-changing decision model for heterogeneous traffic. This unique tool uses the both concept of Fuzzy Logic and Artificial Neural network with training facilities. This model is based on the notion that the drivers make lane-changing decisions based several interlinked parameters. This model structure is flexible enough to accommodate any further parameter and training, particularly to reflect the local condition and traffic behavior.

However this model is very basic in structure. Modeling the cooperative lane-changing behaviors (e.g. courtesy yielding) has not been included within the scope of this research. Future research should capture the effects of cooperation among driver, particularly in the merging areas near the on ramps. The interaction between the lane-changing and acceleration behavior of the driver is also ignored in the current model whereas, in real world, drivers are likely to accelerate and decelerate based on their tactical short-term plan to reach their target lane. Hence, there is the need to develop more detailed driving behavior models based on the concept of generalized target lane that is capable of capturing the interdependencies between lane-changing and acceleration behaviors. It is also important to experiment in various diversified situations especially in situations where time pressure is a dominant factor. As Bowman and Ben-Akiva (1997) pointed out, these choice models "can be challenged as to the validity of their decision protocol". Fuzzy set theory neither explains the mechanism nor accounts for the high variability which results from personality and momentary changes in driving styles and increasing internal aggression due to time pressure.

More specific emerging topics for future research include the factors that govern the size and content of the individuals' associative memory; what, how much, and in which order the individual retrieves the information from that memory. Further, how such factors relate to the number of practiced comparisons? These possible research directions require, above all, the development of methods to obtain data on choice processes in an unobtrusive way. So there is a lot scope to work further in this arena.

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