Use of Multiobjective Genetic Rule Selection for Examining the Effectiveness of Inter-Vehicle Communication in Traffic Simulations

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***Abstract*:** Recently, Inter-Vehicle Communication (IVC) has actively been studied to avoid traffic congestion. In this paper, we propose an idea of using fuzzy rules to examine the effectiveness of IVC. In the proposed approach, we first collect travel records (e.g., travel time, travel path, traffic volume) of vehicles with IVC from our cellular automata-based traffic simulator. Various kinds of available information for vehicles with IVC are used in the antecedent part of our fuzzy rules. The level of the effectiveness of IVC is discretized into four categories (i.e., four classes) in this paper. The consequent class of each fuzzy rule is one of those four classes. Next we generate a large number of fuzzy rules from the collected data. Then we select only a small number of fuzzy rules by multiobjective genetic rule selection. We use three objectives: to maximize the accuracy, to minimize the number of selected rules, and to minimize the total rule length (i.e., the total number of antecedent conditions). Our approach can find a number of non-dominated fuzzy rule-based systems with respect to their accuracy and complexity. Finally we analyze the effectiveness of IVC using fuzzy rules in the obtained fuzzy rule-based systems through their linguistic interpretation.

Keywords: Multiobjective genetic rule selection, fuzzy rules, inter-vehicle communication, traffic simulation.

I. INTRODUCTION

Vehicles are widely used as a means of useful transportation in the mobility society where the demand for road traffic is expanding year by year. At the same time, chronic traffic congestion has become a social problem. To solve this problem, several studies [2], [3] have pointed out and discussed the potential ability of direct wireless communication between vehicles, usually referred to as Inter-Vehicle Communication (IVC). IVC has several advantages: no need of huge public infrastructure investment and little time lag on transmitting traffic information. This is because vehicles can directly communicate traffic information to each other.

In this paper, we propose an idea of examining the effectiveness of IVC using fuzzy rules generated from traffic simulations. During our simulations, we collect time-series data from each vehicle such as the traffic volume and the route of each vehicle. We use fuzzy rules selected by multiobjective genetic rule selection to examine the effectiveness of IVC. A large number of fuzzy rules are generated from the collected data from vehicles. Only a small number of fuzzy rule are selected by multiobjective genetic rule selection. A number of non-dominated fuzzy systems can be obtained with respect to their accuracy and complexity. Using the selected fuzzy rules, we can manually analyze how each vehicle can predict the travel time for each route based on the available information through IVC.

This paper is organized as followed. First we explain our traffic simulator in Section II. Next we explain a route guidance method based on the traffic information sharing among neighboring vehicles through IVC in Section III. Then we explain multiobjective genetic rule selection in Section IV. In Section V, we examine the effect of IVC through computational experiments on our traffic simulator. Experimental results show that the selected fuzzy if-then rules can explain how each vehicle chooses a route using the available information through IVC. Finally Section VI concludes this paper.

II. TRAFFIC SIMULATOR

In this section, we explain our traffic simulator. This model is used in Section IV to examine the effect of IVC through computational experiments.

Traffic simulators can be divided into macroscopic and microscopic models. In this paper, we develop a microscopic traffic simulator using cellular automata [6]. Figure 1 shows the road map of our traffic simulator. The simulation area is divided into squared cells. In our simulator, we assume that the road map is treated as a directed graph where a node and a link correspond to an intersection and a road between intersections, respectively. A link is represented by a sequence of gray cells in Fig. 1. The origin and the destination of a driver are assigned randomly to any cell on any link in Fig. 1. When a driver arrives at its destination, a new destination is assigned randomly.

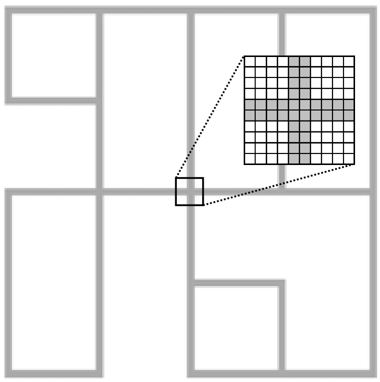

Fig. 1. Road map of our traffic model.

The positions of all vehicles running in the simulator are updated synchronously. At every state transition time, each vehicle stays at the current cell or jumps to its next cell according to a local transition rule. Our local transition rule is simply stated as "a vehicle moves only when its next cell towards its destination is empty".

III. INTER-VEHICLE COMMUNICATION

In this section, we explain a route selection method based on available information for vehicles through IVC. Our method chooses a route for a driver from its origin to its destination based on available information, and revises the selected route whenever the driver approaches an intersection. In this paper, we represent the traffic information for each link by a link weight. For example, if a link weight is large, a vehicle on the link needs long travel time to pass the link. We employ Dijkstra's algorithm [1] to search for the route with the minimal sum of link weights (i.e., the fastest route).

Each driver has its own weight for each link. The actual travel time of the driver is assigned as the weight to the corresponding link. There are two cases where the weight of a link is updated. One is when the driver travels the link. When the driver arrives at a node (i.e., intersection), the weight of the corresponding link is updated to the actual travel time. The update time for the link weight is set as well. The other is the case in which another vehicle is in the range of IVC. Each vehicle compares the update times for all weights with those of another vehicle. Figure 2 shows an example in which a vehicle A passes on another vehicle B on the opposite lane. They can communicate with each other through IVC. Traffic information to be shared by these two vehicles consists of the travel time (i.e., weight) and the update time for each link. It should be noted that each vehicle has its own travel time and update time for each link. More specifically, the newer information for each link is shared by these two vehicles by updating the older one for each link. Closely adjacent vehicles in the same lane also communicate directly with each other in the same manner as in the above-mentioned situation.

A (before)

# of link	Travel time	Update time
1	7	7
2	5	12
3	8	20
4	3	23

A (after)

# of link	Travel time	Update time
1	5	25
2	6	20
3	8	20
4	3	23

B (before)

# of link	Travel time	Update time
1	5	25
2	6	20
3	9	14
4	5	5

B (after)

# of link	Travel time	Update time
1	5	25
2	6	20
3	8	20
4	3	23

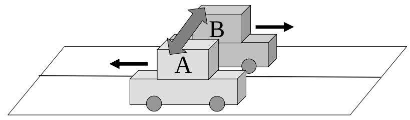

Fig. 2. An example of inter-vehicle communication.

IV. MULTIOBJECTIVE RULE SELECTION

In this section, we briefly explain fuzzy rules, fuzzy reasoning, and multiobjective genetic rule selection.

1. Pattern Classification Problem

Let us assume that we have m training (i.e., labeled) patterns $\mathbf{x}_p = (x_{p1}, ..., x_{pn})$, $p = 1, 2, ..., m$ from M classes in the n-dimensional continuous pattern space where x_{pi} is the attribute value of the p-th training pattern for the i-th attribute ($i = 1, 2, ..., n$). For the simplicity of explanation, we assume that all the attribute values have already been normalized into real numbers in the unit interval [0, 1]. That is, $x_{pi} \in [0, 1]$ for $p = 1, 2, ..., m$ and $i = 1, 2, ..., n$.

2. Fuzzy Rules for Pattern Classification

We use fuzzy rules of the following type for our n-dimensional problem:

$$\text{Rule } R_q: \text{If } x_1 \text{ is } A_{q1} \text{ and ... and } x_n \text{ is } A_{qn} \text{ then Class } C_q \text{ with } CF_q, \tag{1}$$

where R_q is the label of the q-th fuzzy rule, $\mathbf{x} = (x_1, ..., x_n)$ is an n-dimensional pattern vector, A_{qi} is an antecedent fuzzy set ($i = 1, 2, ..., n$), C_q is a class label, and CF_q is a certainty grade.

We use multiple fuzzy partitions with different granularities in rule extraction. In this paper, we use four homogeneous fuzzy partitions with triangular fuzzy sets in Fig. 3. In addition to the 14 fuzzy sets in Fig. 3, we also use the domain interval [0, 1] as an antecedent fuzzy set in order to represent a *don't care* condition. That is, we use the 15 antecedent fuzzy sets for each attribute in our computational experiments. Thus the total number of possible fuzzy rules is 15^n.

For each of those 15^n combinations of the antecedent fuzzy sets, the consequent class and the certainty grade can be easily specified based on compatible training patterns [4]. Using a fuzzy rule evaluation measure in fuzzy data mining [4], we generate a prespecified number of fuzzy rules.

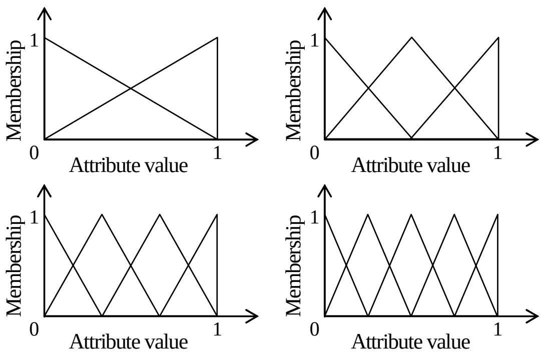

Fig. 3. Four fuzzy partitions used in our experiments.

3. Multiobjective Genetic Rule Selection

Let us assume that N candidate rules have already been extracted. Multiobjective genetic rule selection tries to find an accurate and compact rule set from the N candidate rules. Any subset S of the N candidate rules can be represented by a binary string of length N as $S = s_1 s_2 s_3 \cdots s_N$ where $s_i = 1$ and $s_i = 0$ mean that the i-th candidate rule is included in and excluded from the rule set S, respectively. Such a binary string is used as an individual in multiobjective genetic rule selection.

We use an evolutionary multiobjective optimization (EMO) algorithm to search for non-dominated fuzzy rule sets with respect to the three objectives: to maximize the number of correctly classified training patterns by S, to minimize the number of fuzzy rules in S, and to minimize the total rule length of S.

Since each individual is represented by a binary string, we can use any EMO algorithm with standard genetic operations. In our computational experiments, we used NSGA-II together with uniform crossover and bit-flip mutation. The execution of NSGA-II was terminated at the prespecified number of generations. See [5] for details on multiobjective genetic rule selection.

V. COMPUTATIONAL EXPERIMENTS

1. Data Preparation

In this subsection, we explain how to prepare training data with class labels from the travel records in our traffic simulator. There exist 300 vehicles in our simulation environment in Fig. 1. The termination condition of traffic simulations was that each vehicle reached the goals at least 50 times. Each vehicle can communicate with another vehicle in the eight neighborhood cells.

Let us assume that a vehicle travels from node A to B and then chooses a route from node B to C in Fig. 4. In this case, a training pattern $\mathbf{x} = (x_1, \ldots, x_{10})$ is collected at the node B. In the following, each element of this training pattern is explained in detail.

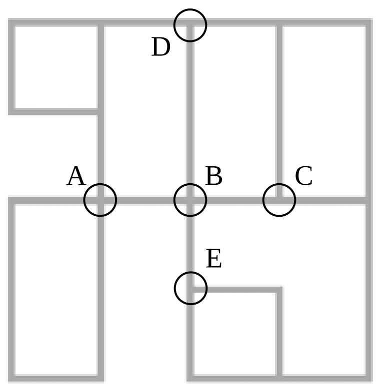

Fig. 4. An example of *link connection density*.

The first three elements x_1, x_2, and x_3 are *link connection density* of node A, B, and C, respectively. *Link connection density* is a sum of the number of links that the neighbor nodes have. For example, x_2 is *link connection density* of node B, which is a sum of the number of links that the neighboring nodes (i.e., A, C, D, and E) have. That is, x_2 is 13 (i.e., 4+3+3+3). When the *link connection density* of a node is high, the node can be viewed as a hub of the neighboring nodes. That is, a large number of vehicles must be likely to pass the node.

The fourth element x_4 is the traffic volume in the current lane (i.e., A to B), x_5 is the traffic volume in the current opposite lane (i.e., B to A), x_6 is the traffic volume in the next lane (i.e., B to C), and x_7 is the traffic volume in the next opposite lane (i.e., C to B). A large traffic volume of a link means heavy traffic where each vehicle can communicate with each other very often. It also suggests possible traffic congestion.

The other elements x_8, x_9, x_{10} are the number of links of nodes A, B, and C, respectively. They are related to the traffic volume and the frequency of communication.

Next we explain how to define the class label of each training pattern, which shows the effectiveness of IVC. We focus on the freshness of traffic information held by each vehicle and the accuracy of the predicted travel time from available information. We use the following four class labels:

Class 1: The update time of the weight of the chosen link held by a vehicle is old, and the vehicle could not correctly predict the travel time of the chosen link.

Class 2: The update time is old, but the vehicle could correctly predict the travel time.

Class 3: The update time is new, but the vehicle could not correctly predict the travel time.

Class 4: The update time is new, and the vehicle could correctly predict the travel time.

2. Experimental Results

First we generated 250 fuzzy rules for each class from the collected training patterns. Those fuzzy rules were used as candidate rule in multiobjective genetic rule selection where NSGA-II with the population size 200 was executed fro 5000 generations.

We obtained a number of fuzzy systems with different accuracy-complexity tradeoffs from a single run of NSGA-II. In order to manually analyze the effectiveness of IVC, we chose a very simple fuzzy system with only a single rule per class in Fig. 5 where DC means *don't care* and the real number in the parentheses shows the certainty grade of each fuzzy rule. The selected fuzzy rules in Fig. 5 are linguistically interpreted as follows:

R_1: If a vehicle came from a node with high *link connection density* and the traffic volume in the current link is moderate, it cannot obtain new traffic information and cannot predict the travel time.

R_2: If a vehicle is about to go to a node with moderate *link connection density* and the traffic volume in the current link is very large, it can obtain new traffic information but cannot predict the travel time.

R_3: If a vehicle is on a link with a very light traffic, the vehicle cannot obtain new traffic information but can predict the travel time correctly.

R_4: If a vehicle came from a node with small *link connection density* and is on a link with a somewhat heavy traffic, it can use new traffic information and can predict the travel time correctly.

From these fuzzy rules, we can see that there exist situations where vehicles cannot obtain new traffic information by IVC. We can also see that there are some cases in which vehicles cannot predict their travel times even when they have new information.

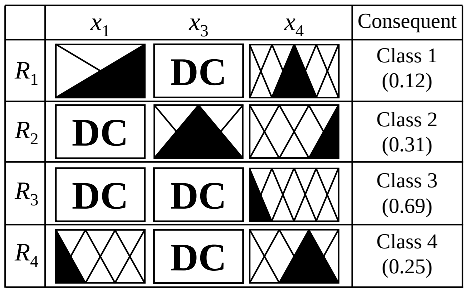

Fig. 5. One example of extracted knowledge.

VI. CONCLUSION

We proposed an idea of using fuzzy rules to examine the effectiveness of Inter-Vehicle Communication (IVC). Through computational experiments, we demonstrated that we can obtain linguistic descriptions from fuzzy rules about the characteristic features of IVC with respect to the availability of new traffic information and the accuracy of predicted travel times for vehicles.

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