Agent Modeling with Individual Human Behaviors

(Extended Abstract)

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ABSTRACT

The challenge presented in this paper is to obtain a human-like individual behavior model by using participatory modeling technology in the traffic domain. We show a methodology that can elicit prior knowledge for explaining human driving behavior in specific environments, and then construct a driving behavior model based on of a set of prior knowledge. Since, in the real world, human drivers often perform unintentional actions, and occasionally they have no logical reason for their driving actions, we are forced to construct a behavior model with an insufficient amount of prior knowledge. To construct an individual driving behavior model with insufficient knowledge, we take the approach of using knowledge from others to complement the lack of knowledge from oneself.

Categories and Subject Descriptors

I.2.11 [**Distributed Artificial Intelligence**]: Multiagent systems

General Terms

Design

Keywords

multiagent simulation, modeling methodology, traffic simulation, participatory modeling

1. INTRODUCTION

The challenge presented in this paper is to use participatory modeling technology to obtain a human-like behavior model in the traffic domain. Participatory modeling is a promising technology with which to obtain individual behavior models based on actual human behavior. A human driver controls his/her car based on his/her driving style. We want to construct a driver agent model that can reproduce diverse driving styles. Trying to achieve that with participatory modeling technology raises difficulties when trying to explain a sequence of driving behaviors. Because, in the real world, a human driver occasionally performs unintentional actions, we cannot obtain sufficient prior knowl-

Figure 1: 3D Virtual Driving Simulator

edge to explain his/her driving behavior. To permit a driver agent model to be created even though the knowledge is insufficient, we take the approach of using complimentary prior knowledge from other drivers. This approach allows us to acquire a driving behavior model that is fleshed out (patched) by knowledge from others.

2. DRIVER AGENT MODELING

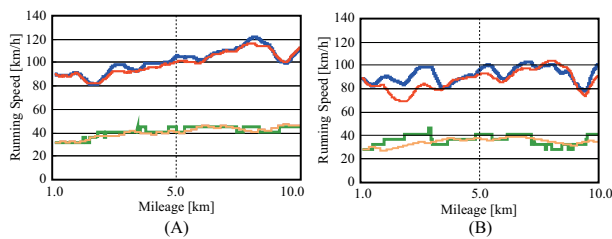*Collecting Driving Log on Virtual Driving Simulator.*

We use a 3D virtual driving simulator (see Figure 1)[1], which can offer 11km virtual highway, to collect realistic driving log data from humans. Such simulations are often used to train drivers, and so our simulator is expected to yield realistic driving data. We can get information on transitions in running speed, acceleration, and the usage of accelerator/brake.

Identifying individual behaviors with domain expert.

We investigated the collected driving log data to identify each subject's individual driving behavior. For the investigation, we use the following data collected for each subject: mileage(km), speed(km/h), acceleration(m/s), and Usage of acceleration(%). We try to capture an individual's behavior by investigating his/her driving log data. In particular, the speed/acceleration transitions provide a lot of useful data. Different drivers have different driving styles, even in identical conditions.

Interview of Subjects.

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[1]This 3D virtual driving simulator is located at Graduate School of Engineering Division of Global Architecture, Osaka Univ., JAPAN

Figure 2: Transitions in running speed and acceleration

We interviewed the subjects after they participated in the driving simulation. The purpose of the interview was to gather information on their specific operations, identified in the previous step, for generating prior knowledge. In the interview, we asked each subject about the four points for each specific operation: reason/motivation for the operation, target of subject's gaze, recognized target, and evaluation of the recognition. Our analyses of the interview log and charts yielded information on the subjects' operations under a range of conditions, *i.e.*, "sense-act" information. We use such information as prior knowledge and represent it as driving rules, each of which denotes a driving operation made under a certain condition.

The obtained knowledge is represented using formal expressions based on predicate logic. After a discussion with traffic engineers, we fixed some predicates to represent prior knowledge. These predicates are also used to formally describe the observations extracted from the driving log data. An observation describes what the subject noticed, and how he/she operated his/her car in the situation presented.

Construction of Driving Behavior Models.

We applied a modeling method based on hypothetical reasoning [1] to acquire a driving behavior model of each human subject. The major steps of the model acquisition algorithm are as follows.

1. The driving model $\mathcal{M} = \langle P, \preceq \rangle$ at time $t-1$ is input. P is a subset of *Rules* which is the set of rules obtained from all subjects, and $\preceq$ represents the priorities of each rule in P

2. If the target subject continues the same driving operation as at time $t-1$, the algorithm just returns $\mathcal{M}$.

3. If the subject initiates a new operation at time t, a driving rule p, which is applicable to the environment at t (E_t) and can explain the action observed at t, is chosen from P. p is assigned higher priority than all other rules applicable to E_t in P ($\preceq$ is updated to $\preceq'$); finally, $\mathcal{M} = \langle P, \preceq' \rangle$ is returned. The goal of the algorithm is to obtain a minimal explanation. Therefore, the algorithm first tries to find an applicable rule in the current P to avoid adding another rule.

4. If there is no applicable driving rule in P, a driving rule p, which is applicable to E_t, is chosen from *Rules*. p is assigned higher priority than all other rules applicable to E_t in *Rules* ($\preceq$ is updated to $\preceq'$); finally, $\mathcal{M} = (P \cup \{p\}, \preceq')$ is returned.
If $P \cup \{p\}$ is inconsistent, the algorithm returns "*fail*".

Speed		Average	Standard Dev.	Correlation
S_1	Subject	100.9	10.6	0.96
	Agent	95.8	9.1	
S_2	Subject	91.6	7.18	0.71
	Agent	86.8	9.5	

Table 1: Compare subject's log data with corresponding agent's log data

3. EVALUATION AND DISCUSSION

We show some examples of the driving behavior models so acquired and the experimental results. Figure 2 shows transitions in running speed and acceleration of the subjects and their corresponding driver agents. In Figure 2, the bold blue line and bold green line plot subject's running speed and acceleration, respectively. The thin red line and thin orange line represent driver agent's running speed and acceleration, respectively.

Case 1 for S_1:.

The driving behavior model of subject S_1 consists of 6 driving rules and the relationships defining their priorities. The road section of the first 7km is a gentle ascending slope with some curves. S_1 drove under his/her desired speed (120km/h) in this zone (see Figure 2(A)). S_1's behavior model can reproduce his/her driving log by the application of three rules, which are used to increase the running speed. After the 7km point, the road curves downhill. Because S_1's model does not include a rule to release the accelerator, at first, the running speed is continuously increased. However, once the speed exceeds the desired speed, the accelerator pedal is released. If the speed becomes too slow, this model can recover because a rule, which is used to speed-up when car speed becomes too slow, is prioritized over other rules which are used to release the accelerator in a curve.

Case 2 for S_2:.

The driving behavior model of subject S_2 includes 8 driving rules. In Figure 2 (A) and (B), S_2's behavior looks similar to S_1. The difference is apparent around 7km - 9km region. S_2 drove at around 100km/h while S_1 exceeded 100km/h. S_2's model can reproduce this difference in driving behavior. It includes a rule, representing "if the subject sees a downhill ahead, he/she releases the accelerator." Therefore, S_2's model lowers the speed. This is one example of realizing individuality in driving style.

In Table 1, we plot the average and the standard deviation of the running speed of three examples. Again for S_1 and S_2, the acquired models are accurate.

4. CONCLUSION

In summary, the contributions of this paper are to (1) propose a novel agent modeling methodology for realizing individuality in agent behavior, (2) introduce an approach that can offset knowledge shortfalls for agent modeling, and (3) provide a hint for constructing driver agents for realistic traffic simulations.

5. REFERENCES

[1] Y. Murakami, Y. Sugimoto, and T. Ishida. Modeling human behavior for virtual training systems. In *Proceedings of the 20th National Conference on Artificial Intelligence (AAAI-05)*, pages 127–132, 2005.