Intention Recognition Using Case Base Learning For Driver Support System

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Abstract*-Many traffic accidents are caused by driver's carelessness with lack of information surrounding vehicle. In order to prevent the accident, it becomes important to carry out dangerous warning in advance to a driver. In this paper, the intention recognition model of the driver by case base learning is proposed. In order to recognize an intention (left turn, right-turn, or going straight) of a driver, direction of a driver's face, the speed of a car and distance to intersection are detected. Using them as a case node performs intention recognition. Arranging a case node performs inductive study, and the rate of recognition improves by the increase in a study example. By this method, PC can hold an intention of a driver in early stages, and give warning in display before action.*

In Japan, about 9000-people die per year in traffic accidents, and the number of accidents are also increasing. The main cause that causes traffic accidents are based on the lack of information of the surroundings, such as delay of recognition and misjudgment.

1. Introduction

ITS (Intelligent Transport Systems) is a new traffic system aiming at solution of road traffic problems, such as a traffic accident and traffic congestion, by carrying out the network of people, a road, and the vehicles using information using the latest information communication technology. It is expected as a system that aims at better comfortable nature and better safety. When the dangerous phenomenon that may cause a traffic accident is the fundamental action, which a driver "recognize" a dangerous phenomenon, make a "judgment" to avoid, and to "operate". In order to prevent the accident, a prior dangerous warning becomes important.

In this paper, the intention recognition model for driving support system is proposed in a humane vehicle. A humane vehicle is a traffic system centering on man, and man's safety and comfort ITS are observed. Since an intention recognition model recognizes an intention of a driver, it can show only the information which a driver needs. Therefore, since information oversupply can be prevented, it is connected with decreasing a driver's burden. The intention recognition mechanism makes the case node from direction of a driver's face, speed of a car, and distance to intersection. Arranging a case node performs inductive learning, and the rate of recognition is improved by the increase in a learning example.

2. Architecture of Intention Recognition Model

As explained in the introduction, the approach of our first step is to build a system model. Here, we take some important Fuzzy concepts. In this section, at first we introduce these Fuzzy concepts, and later we will explain how the intention recognition model was established.

2.1 Definition of conceptual Fuzzy sets

In this paper, the knowledge representation of a conceptual fuzzy set (CFS) is used as the technique of the knowledge construction about an intention of the human being who is an fuzzy concept. CFS has the following two characters.

1) The fusion processing of the sign that the digital data and human being of the real world think of can be carried out.
2) The bottom up processing to a high order concept from the amount of physics and the top-down processing to the amount of physics from a high order concept can be united.

CFS also has the mechanism with it fuzzy knowledge is not only expressed in distribution on the associative memory, but in which it performs fuzzy knowledge processing using the remembrance process of an associative memory. Moreover, since CFS is realized by the associative memory, merits, such as complicated processing by treatment and multilayer combination of situation dependability, are obtained.

The label of a fuzzy set is expressing the name of a concept and the form of a fuzzy set is expressing the meaning of a concept. If a semantic use theory is followed, although other language will express the meaning of the word, the meaning changes with the times of use. Therefore, if the cautions range at the time of use is expressed with the activity value which accompanies language, the fuzzy set formed by other language can express the meaning of ambiguous language. This distributed knowledge representation is called CFS (Fig. 1).

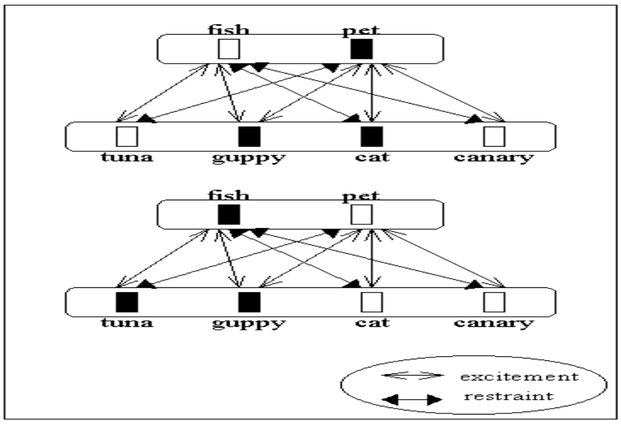

Fig.1 Conceptual Fuzzy Set

Since the distribution of this activity value changes depending on various situations, it can express change of the meaning by the situation. Moreover, since not only logic expression but a knowledge representation is possible for CFS, it can also express clearly logically the thing in which an explicit knowledge representation is impossible. The activity value of CFS is controlled by the associative memory. Then, a node expresses a concept and a link corresponds to the strength of the relation between concepts. If the node of the concept by which semantic expression should be carried out is activated, via the network built beforehand, an activity value will spread and echo operation will take place. This echo operation stops in the place where system energy became the minimum, and the conceptual node of the side that expresses a meaning as the result is recollected by the form activated in a certain grades. The distribution of the activity value that appears here is a fuzzy set.

CFS is functionally built using a neural network's study rule. That is, according to the example of conceptual expression, the link between nodes is corrected using the Hebb study rule of a formula (1).

$$\dot{m}_{ij} = -m_{ij} + a_i b_j \cdots (1)$$

Other unnecessary concepts are not activated by conceptual explanation in CFS. Therefore, structural study including selection of a node will be performed even from the redundant explanation element. Moreover, in case we usually form the concept, the overall concept is formed in CFS, combining sequentially each concept formed separately like. In fact two or more CFS are compoundable according to a formula (2).

$$M = -m_{ij} + a_i b_j \cdots (2)$$

However, Norm is a certain kind of normalization.

2.2 Fuzzy Associative Reasoning

A network is constituted using Bi-directional Associative Memory (BAM) which is an associative memory neural network's kind two or more, and it reasons by repeating propagation of an activity value (echo operation). Here, the explanation about the fuzzy associative memory system that systematized BAM used as the foundations of associative reasoning is shown.

2.3 Fuzzy Associative Memory System

BAM is the network that is composed of 2 layers as shown in Fig.2. More than one node exists in each layer and the weight of the combination among the nodes is expressed by associative matrix of $M \in R^{n*p}$. For layer $L_{A,} L_B$, if this associative matrix remembers the pattern pair of $A \in R^n, B \in R^p$,even if L, layer includes noise and $A' \in R^n$ is inputted, in L_B layer, B can be recalled by reverberation among layer. Oppositely, even if L_B includes noise and $B' \in R^P$ is inputted, A can be recalled in L_A layer.

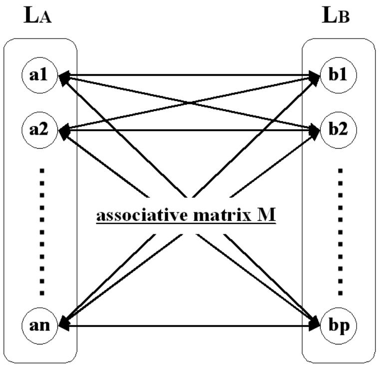

Fig.2 Network of BAM

The system shown in Fig.3 has if layer and a then layer. Because the correlation between the if layer and a then layer exceeds the agreement of BAM can be memorized, one node sets the rule layer which represents one rule. Therefore, the fuzzy rule can be expressed in building BAM between if layer and the then layer..

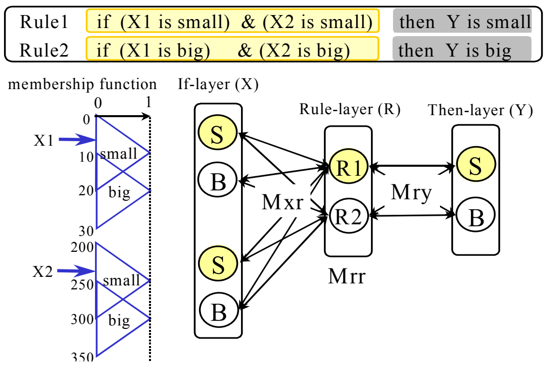

Fig.3 Fuzzy Associative

Fig.4 shows the necessary knowledge to build associative memory.

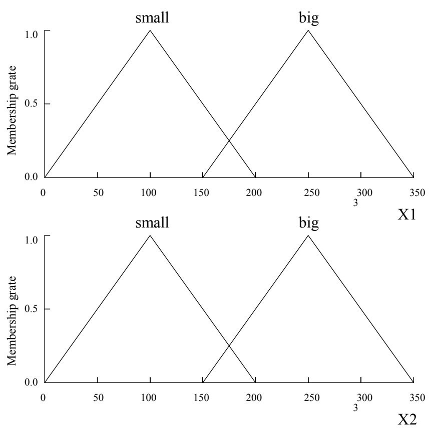

Fig.4 Membership Function

2.4 Model of Intention Recognition by Case-Based Learning

As the technique of the knowledge architecture about intention of the human being is an ambiguous concept, we show the research, which uses knowledge expression of CFS.

In the knowledge information processing using CFS, processes of bottom-up and top down are performed complementarily and simultaneously. By the intention recognition, the knowledge about context is placed in the high rank layer, and the concrete instance is placed in the low rank layer. The concept of high rank layer is described by the concrete instance in the low rank layer. When the characteristic quantity of recognition object is obtained, nodes that correspond to each characteristic quantity of the lower rank layer are activated, and the concept node of high rank layer is activated too. At the same time, the activity of lower rank layer nodes that contradict the context in the high rank layer is restrained, and the activity of nodes that can be consented is promoted. In this way, not only the characteristic shows concrete instance, but also context is activated. Even in the case that characteristic includes noise and recognition is wrong, by the context helping recognition. The system can exclude ambiguousness and find out a right result. This recognition determined by context is called context sensitive recognition.

The intention recognition model (Fig. 5) which recognizes 3 basic operation action intention of going straight, the right-turn, and left turn of an operation intention from operation of a face, the speed of vehicles, and position information is explained below.

This model is loaded into Fuzzy Association memory system and association reasoning is executed. It is composed of 3 layers. The lowest layer is the entry layer and expresses the characteristic quantity of each operation by the membership value of the fuzzy label. The middle layer arranges the case node that shows case to be used in the process of the learning. Since it learns 3 operations for each case, totally it learns 3N patterns for N cases. In the middle layer, when the characteristic of each operation is input, the node of human being that has the most similar characteristic is activated. By the activated value distribution, we can tell the corresponding case for the operation in each part. However, only with the activated value, which appears in the middle layer, the operation intention can't be determined. This problem is solved by the introduction of context. The top layer shows operation intention and consists of three nodes corresponding to turning left, going straight and turning right respectively. The top layer is combined with all nodes of middle layer.

3. Experiment of Intention Recognition Using Case Base Learning

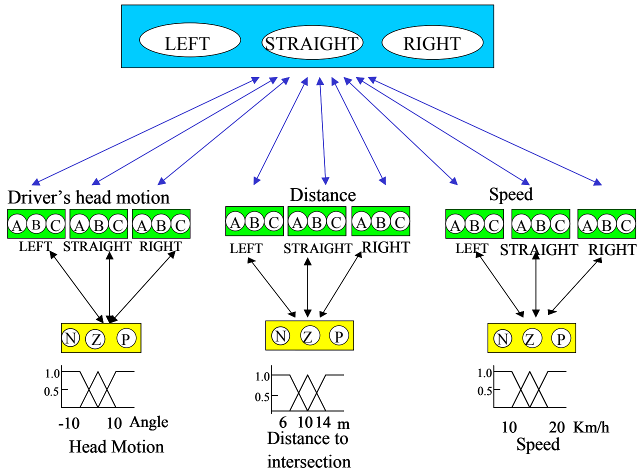

Fig.5 Intention Recognition Model

3.1 Driving Operation and Intention Recognition

When some operations are performed, a series of operation determined by the grade is checked. An operation intention is reasoned by detection of the kind of these operation. The following actions are taken when a driver wants to bend on the left. The front is seen, a left mirror is checked and speed is reduced. A left blinker is then attached and a left is checked again. And a wheel is turned to the left. A camera and PC detect these operation and send them to the basis of the server which reasons an intention. Intention recognition is effective in order to support operation in an early stage like before attaching a blinker. In order to send an intention of a driver to other cars and pedestrians and to acquire required dangerous information from the circumference in that case, it is very important to recognize the intention of a driver as early as possible.

3.2 Experiment System

An intention recognition experiment system is shown in Fig. 6. The CCD cameras agent1 and agent2 for this system detecting operation of a driver's face and the distance to a crossing and PC (agent3) for detecting speed of a car are contained. Agent1, and Agent2 and Agent3 send each data to a server with the intention recognition model. In order to detect the data of operation of a face, and the position of a car, I-space was used for the experiment. I-space is the software that can pursue movement and the position of an object by sexual desire news.

As for an experiment, vehicles go straight on toward a crossing. The position information on the vehicles at this time

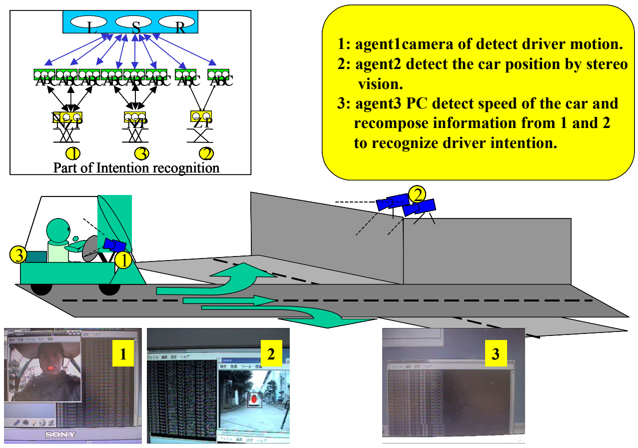

Fig.6 Experiment System

is acquired with the camera currently installed in the crossing. The direction information on a driver's face and the speed information on vehicles are acquired simultaneously, intention reasoning is performed using a fuzzy associative memory system, and a driver recognizes an intention for whether it is going to turn at whether it is going to go straight on whether it is going to bend on the right on the left. Moreover, improvement in the rate of recognition is aimed at by increasing a study example.

In this paper, as shown in Table 1, it experimented by choosing the characteristic basic operation action data of Japanese 7 pattern. It accumulated to the middle class who shows these examples in Fig. 7.

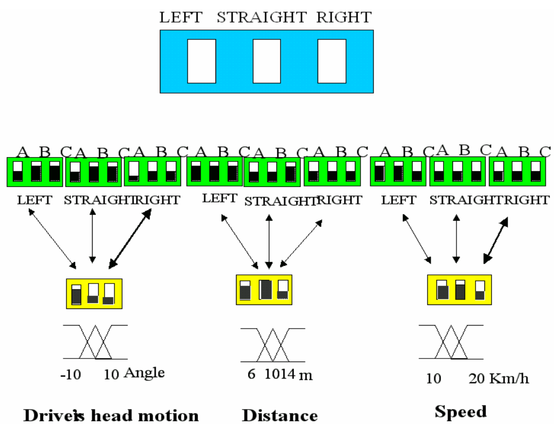

Fig.7 Recognition Result(No Context)

Table.1. Operation action and intention

operation				intention
pattern	head motion (width)	distance	speed	
A	large	far	middle	left
B	middle	middle	fast	left
C	small	far	middle	left
D	large	near	middle	left
E	middle	near	fast	left
F	small	near	fast	left
G	middle	near	slow	left
A	middle	middle	fast	right
B	small	far	middle	right
C	middle	near	fast	right
D	small	near	fast	right
E	middle	near	middle	right
F	middle	middle	middle	right
G	small	middle	middle	right

When the data with which operation action is not learned is inputted into this intention recognition model, the result obtained without using a context is Fig. 7. In this result, the activity value distribution of a middle node is ambiguous and cannot judge which operation intention it is. On the other hand, Fig. 8 is the result of using a context. A node activity value distribution is converged on LEFT by echo operation of BAM. Thus, when an input value and the first activity state are ambiguous, it converges on the state where the activity value distribution was dependent on the context with echo operation.

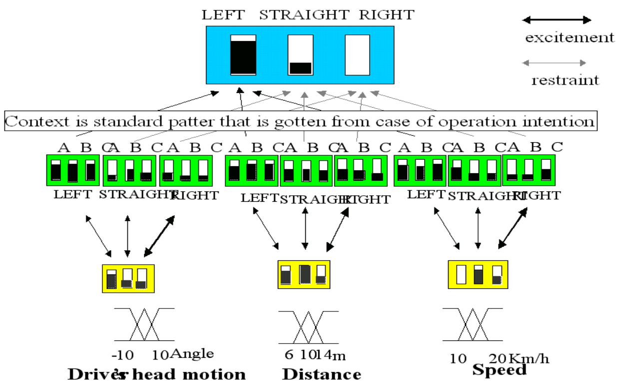

Fig.8 Recognition Result(Using Context)

3.3 Experimental Result of Intention Recognition by the Case Base Learning

The result of the number of the study examples based on seven nodes and the rate of recognition that were shown in Fig. 6 is shown in graph 1. The rate of recognition is a thing when inputting non-learned operation data. The rates of recognition after making a 7-man-minute example learn were 88% of left turn, 95% of going straight, and 86% of right-turn. This experiment showed the intention recognition model that it was the good way the used case base study recognizes an intention of a driver. It can be said that the intention recognition with more exact than a driver's obtaining many data of operation is shown.

3.4 Simulation of Intention Recognition

That a better recognition result is shown was able to say by adding a driver's data of operation by above-mentioned experiment. Here, three more persons' data of operation was added, and the simulation of intention recognition was performed to the operation of three persons. A result is shown in Table 2.

Table2. Operation action and intention

	Left	Straight	Right
UNIT_A	7/8	5/5	5/6
Rate	87%	100%	83%
UNIT_B	8/8	6/6	5/5
Rate	100%	100%	100%
UNIT_C	7/8	5/5	5/6
Rate	87%	100%	83%

From this result, the good result was shown compared with the time of the way when adding three more persons' data being seven persons.

4. Conclusion

In this paper, the intention recognition model by case base study was proposed. This is based on the conceptual fuzzy set. Ten persons' operations were chosen as model for the operation. By intention recognition of a driver, the rate of recognition improves by the increase in a study example, and it is shown that inductive study was performed. This showed the usefulness of driver intention reasoning of the intention recognition mechanism by the case base.

There is individuality, such as calm operation operated and irritated, calm rough operation, etc., in operation of a driver. When operation of a car is observed, the node is named by taking in ontology to an intention recognition model (Fig.8). By acquired driver's different individuality, we will be able to share common network. Using this model, we have set our future target of operating intention recognition for the pedestrian.

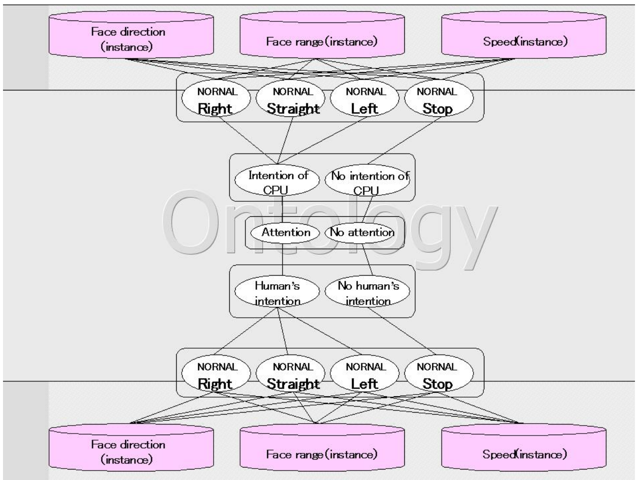

Fig.8 Ontology Model

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