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Rapid Occupant Classification System Based Rough Sets Theory

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Abstract: In the intelligent airbag system, the correct classification of occupant type is the precondition and plays an important role in controlling the airbag release time and inflation strength during emergent accidents. In the paper, the novel rapid occupant classification system is proposed in which tens of pressure sensors are needed to real-time collect pressure distribution data and then the rough sets theory is combined to extract classification knowledge from data features. Furthermore, Experiments have been done to verify its efficiency and effectiviness.

Keywords: Occupant classification, Knowledge, Rough sets, Sensor

INTRODUCTION

Since automotive airbag is widely used in the automobile industry, it indeed plays an important role on preventing the occupant casualties and has saved the lives of countless people (Mao and Qian, 2003). During use, however, there are lots of problems found. For example, due to improper control, the release of airbag may cause a lot of unexpected casualties. In particular, when the current occupants are children, such incidents occur more. To avoid them, the additional Occupant Classification System (OCS) should be added into the automobile control system (Zhu *et al.,* 2011). It can be used to identify whether the occupant is material object or people and if people, it can further determine adults or children. Then, the airbag can be correctly released and provide the best protection for different types of crew (Gao *et al*., 2009).

Nowadays, there is a variety of OCSs based on different classification methods which are mainly vision-based, mass measure, body pressure distribution and electric field sensor technologies. Vision-based method is to extract the human body information from collected images (Jiang *et al*., 2005) and then do classification through pattern recognition or pattern matching (Seyed *et al*., 2007). Mass measure-based is to measure the weight of occupant by use of one or more weight sensors and then by contrast to the threshold, the occupant type is identified. The smart airbags that now had been developed and sold in the market are the types and carry out the occupant classification in accordance with the weight threshold (Zhu *et al*., 2011). The body pressure distribution method is to identify the type of occupant according to the pressure distribution maps about the human body contact with the seat surface. Through comparatively analysis of shape, distribution, width, weight and maximum pressure element parameters (Mao and Qian, 2003), the occupant types are then identified. Moreover, a kind of high-density body pressure distribution measurement system developed by Tekscan Corp is used to classify the occupant types combined with BP neural networks (Dong *et al.*, 2009). The electric field sensor method is to utilize the feature of the electrical conductivity of human to identify the different types of crew (Armin and Dirk, 2008).

In the study, we have introduced a rapid occupant classification system based rough sets theory (ROCS-RS). It is equipped with only tens of pressure sensors. Moreover, the Rough Sets Theory (RST) is applied to obtain classification knowledge from pressure sensor data, which can keep more accurate classification with simpler and cheaper hardware cost.

METHODOLOGY

Architecture: Based on knowledge acquisition, representation and reasoning of knowledge engineering, ROCS-RS carries out knowledge discovering and reasoning, which can effectively solve the problems of traditional occupant classification system, difficult for fast classification and high classification errors. ROCS-RS can do knowledge reduction and reasoning, simulate expert reasoning and actively acquire, integrate knowledge. The architecture is shown in Fig. 1.

The system mainly consists of two parts: a matrix of Pressure sensor and classification mechanism based RST. The matrix is shown in Fig. 2. The Micro Control Unit (MCU) obtains the pressure value of each sensor by the

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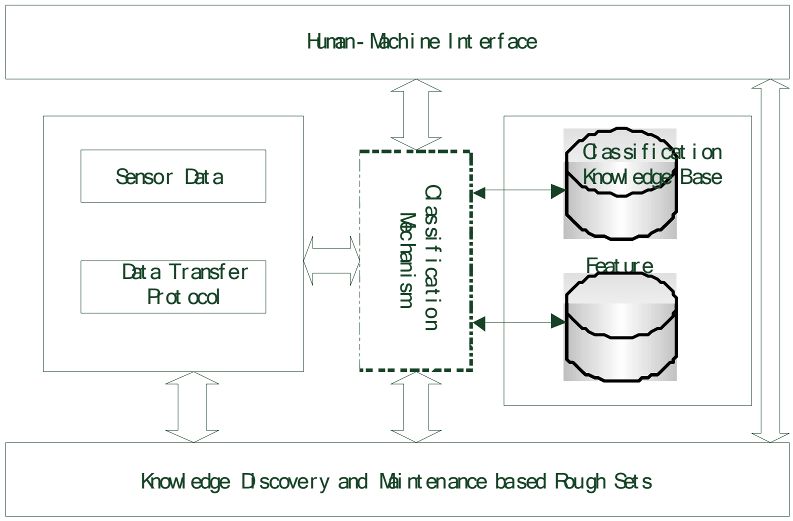


Fig. 1: Architecture of ROCS-RS

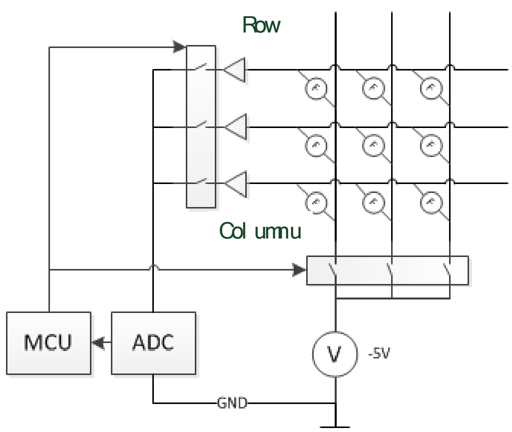


Fig. 2: Pressure sensor matrix

row and column scanning in turn. The column is as switch control and the row is pressure scanning line.

Sensor data analysis:
Shape parameter: A large number of experiments show that the pressure distribution between the human buttocks and seat surface is compact pressure distribution; moreover, the distribution shape of adults and children are different; however, those of general objects on the seat surface are decentralized. The three different types of pressure distribution have been described in Fig. 3(Mao and Qian, 2003).

Fig. 3a is a typical pressure distribution diagram of an adult ride; and Fig. 3b is a typical one of a child; Fig. 3c is the pressure distribution one of a general object. The shape parameter can be obtained by the topological analysis of the pressure distribution on the seat.

Distribution parameter: It is used to characterize the situation of pressure distribution, centralized or decentralized. Fig. 4 indicates a case of decentralized type, which is usually general object.

Width parameter: It mainly classifies occupants based on some bodies' information and usually represents the geometric information related to hips pressure contours.

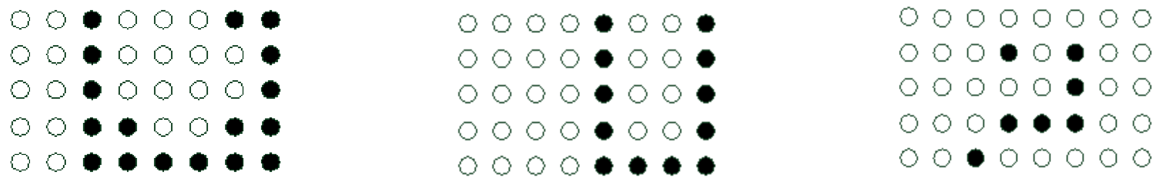
Weight parameter: It is the sum of the total pressure sensors.

Maximum pressure element: Through the pressure values of different sensor elements, the maximum element pressure can be calculated as a reference for subsequent classification.

Knowledge acquisition: The knowledge acquisition steps based on rough sets theory are as follows Pawlak (1997):

- Attribute Reduction. From the point of view of the entire information system, remove the redundant attributes on the basis to ensure that the amount of information dose not reduces.
- Eliminate duplicate rows. Duplicate rows can be considered as the same state, the same decision.
- Reduce Value. For each decision, in the case does not affect the classification and decision ability, the values of certain attributes can be omitted.
- Organize rules. Select the minimum set of rules.

Through experiments, lots of pressure distribution sensor data have been obtained and the feature values are extracted. There are five condition attributes $a_1 \sim a_5$,



(a) Adults (b) Children (c) General objects

Fig. 3: Pressure Distribution Shape

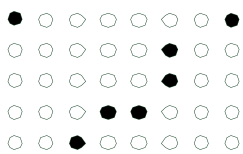


Fig. 4: Decentralized Type

which correspond to the described parameters, shape, distribution, width, weight and maximum pressure element. For shape parameter, value 1 means the pressure distribution is *U* shape and 0 means others; value 1 of the distribution parameter represents the concentrated distribution of pressure elements, 0 for the decentralized; value 2 of the width parameter indicates the width is large, 1 for medium and 0 means small; value 2 of the weight parameter means heavy, 1 is moderate and 0 means small; value 2 of maximum pressure element means big, 1 for moderate and 0 means small. The decision attribute is used to determine the type of occupant and its value 2 represents an adult, 1 for a child and 0 for other object. The quantitative condition and decision attributes forms a two-dimensional table and each row describes a specific determination object for pressure distribution, each column describes a kind of attribute of objects, which is shown in Table 1.

Attribute reduction and Eliminate duplicate rows: The objective of reduction computation is to remove these attributes and attribute values, which mainly includes condition attribute reduction (delete redundant columns) and attribute value reduction (delete redundant attribute values) and eventually form a minimal set of decision rules.

Condition attributes reduction: The discernibility matrix method is adopted to carry out condition attributes reduction. The reduction steps are as follows: compute the discernibility matrix *M*(*S*) of system *S* . *M* (*S*) represents matrix $\lfloor c_{ij} \rfloor n \times n$ with order $n \times n$, where, $\lfloor c_{ij} \rfloor_{n \times n}$ = {a∈A; $a(u_i) \neq a(u_j) \wedge u_i\ u_j \in U$, i, j = 1, 2, ..., n} means(∧ the conjunctive operation) and then we get the discernibility function matrix of the decision matrix table, which is shown in Table 2. In table, the simplified figures are used to represent the properties of columns. Since the matrix is symmetric, only the lower triangular part should be listed. calculate the discernibility function $f_{M(S)}$ related to the discernibility matrix. The expression of $f_{M(S)}$ is the conjunctive of all $\vee c_{ij}$, where, symbol ∧ means the disjunctive operation, and by computation, we obtain calculate the minimum disjunctive normal form of $f_{M(S)}$. Take{a_1, a_3, a_4} as the condition attributes, the reduced decision table is shown in Table 3 which remove the redundant condition attribute a_2 and a_5.

Table 1: Decision classification system

	Condition attributes					
Object set U	a^1	a^2	a^3	a^4	a^5	Decision attributeD
1	1	1	2	2	2	2
2	1	1	1	1	1	1
3	1	0	1	0	0	1
4	1	0	0	0	0	1
5	0	0	2	0	2	0
6	0	1	0	0	2	0
7	1	1	0	1	2	1
8	1	1	2	1	2	2
9	1	0	2	0	1	1
10	0	1	1	2	2	0

Table 2: Discernibility Matrix

1	2	3	4	5	6	7	8	9	10
2	2,4,5								
3	2,3,4	2,4,5							
4	2,3,4,5	2,3,4,5	3						
5	1,2,4	1,2,3,4,5	1,3,5	1,3,5					
6	1,3,4	1,3,4,5	1,2,3,5	1,2,5	2,3				
7	3,4,5	3,5	2,3,4,5	2,4,5	1,2,3,4	1,4			
8	4	3	2,3,4,5	2,3,4,5	1,2,4	1,3,4	3,5		
9	2,4,5	2,3,4	2,3,4,5	3,5	1,5	1,2,3,5	2,3,4,5	2,4,5	
10	1,3	1,4,5	1,2,4,5	1,3,4	2,3,4	3,4	1,4,5	1,3,4	1,2,3,4,5

Table 3 Decision table with removing redundant condition attributes

	Condition attributes			
Object set U	a^1	a^3	a^4	Decision attribute D
1	1	2	2	2
2	1	1	1	1
3	1	1	0	1
4	1	0	0	1
5	0	2	0	0
6	0	0	0	0
7	1	0	1	1
8	1	2	1	2
9	1	2	0	1
10	0	1	2	0

Table 4: Attribute value reduction table of decision rules

Object set U	Condition attributes a^1	a^3	a^4	Decision attribute D
1	1	-	2	2
1'	-	2	2	2
2	1	1	-	1
2'	-	1	1	1
3	1	1	-	1
3'	1	-	0	1
3"	-	1	0	1
4	1	0	-	1
4'	1	-	0	1
5	0	-	-	0
6	0	-	0	0
6'	0	0	-	0
7	1	0	-	1
7'	-	0	1	1
8	-	2	1	2
9	-	2	0	1
9'	1	-	0	1
10	0	1	-	0
10'	-	1	2	0
10"	0	-	2	0

Table 5: One attribute simplification merge of decision rule

Object set U	Condition attributes a^1	a^3	a^4	Decision attribute D
1	1	-	2	2
2	1	1	-	2
3'	1	-	0	1
4	1	0	-	1
5	0	-	-	0
8	-	2	1	2

$$f_{M(S)}(a_1,a_2,a_3,a_4,a_5) = (a_1 \wedge a_3 \wedge a_4) \vee (a_3 \wedge a_4 \wedge a_5)$$

Attribute values reduction: According to the condition attribute reduction table, the attribute value reduction table of decision rules can be further calculated out. Take the attribute value of decision rule 1 for example. Let F = $\{[1]_{a1}, [1]_{a3}, [1]_{a4}\}$, to compute the reduction of F, all subsets $\theta \subseteq F$ should be obtained. For example $[1]_{a1\ a3\ a4}=\{1\}\subset [1]_{D}$, $[1]_{a1\ a3} = \{1, 8, 9\} \not\subset$, $[1]_{D}$, $[1]_{a1a4}$, $[1]_{a1a4} = \{1\}\subset[1]_D$, $[1]_{a3a4} = \{1\}\subset [1]_D$,so one reduction of rule 1 is $a_1a_4 \rightarrow D_1$ or $a_3a_4 \rightarrow D_1$. And so one, the attribute value reduction table of decision rules are obtained which is shown in Table 4.

Formation of minimum decision rule table: Merge from Table 4, a minimum decision rule condition reduction table can be gotten, that is a minimum solution shown in Table 5.

RESULTS AND DISCUSSION

Classification rules from reduction are input into the knowledge base of system. Moreover, the production rules are adopted to represent knowledge based rough sets theory as "mode-action", such as *if*(p_1, p_2 ,..., p_m) then *if* (q_1, q_2, ..., q_n), where, p_1, p_2 , ... , p_m are the condition attributes of rapid occupant classification system, q_1, q_2, ... ,q_n are the decision attributes. According to the minimum solution from Table 5, the classification rules are as follows:

If the pressure distribution shape is *U* and the weight is heavy, then the decision *D* is 2, that is the occupant is an adult.
If the pressure distribution shape is *U* and the weight is moderate, then the decision *D* is 1, that is the occupant is a child.
If the pressure distribution shape is *U* and the weight is small, then the decision *D* is 1, that is the occupant is a child.
If the pressure distribution shape is *U* and the width is small, then the decision *D* is 1, that is the occupant is a child.
If the pressure distribution shape is not *U* and the weight is moderate, then the decision *D* is 0, that is the occupant is a general object.
If the width is large and the weight is medium, then the decision *D* is 2, that is the occupant is an adult.

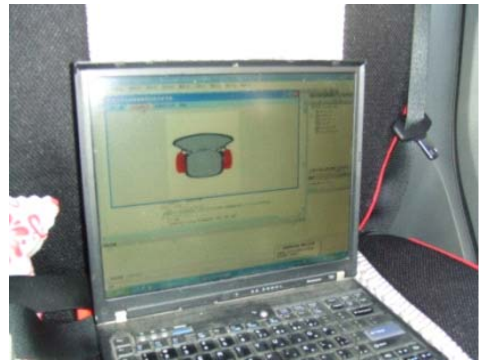


Fig.5: Prototype System

The prototype of ROCS-RS has been developed, which is shown in Fig. 5.

During experiments, there is an adult sitting on the seat and then the pressure distribution shape is *U* width is large and weight is heavy then march the first classification rule in the knowledge base eventually the classification result is an adult after a while there is a child sitting on the set and then the pressure distribution shape is *U* ,width is small and weight is small then march the third classification rule, its classification result is a child. The system interfaces of two experiments are shown in Fig. 6 and 7.

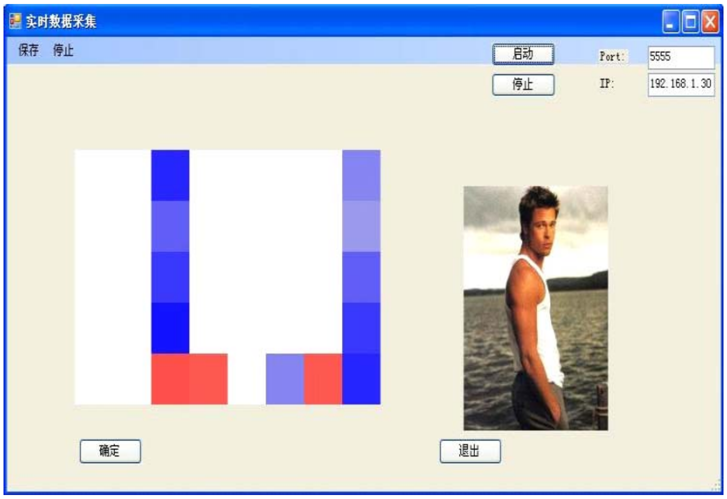


Fig. 6: Classification of adult

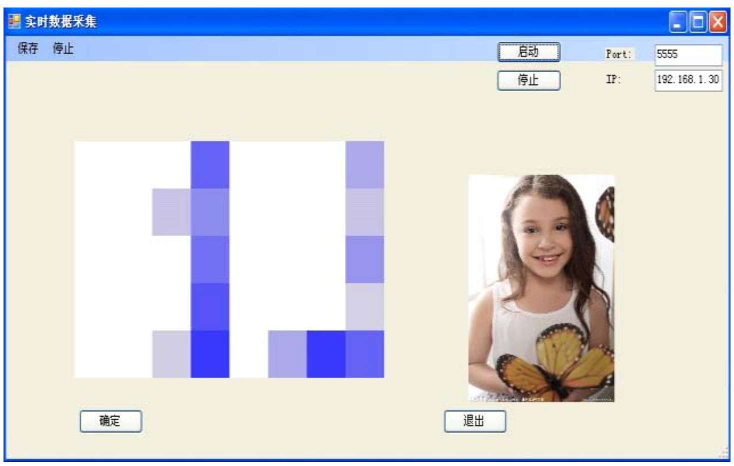


Fig. 7: Classification of children

CONCLUSION

Through accurately analysis of pressure distribution data of different occupants, data features are extracted and classification knowledge are obtained based on RST. The prototype system ROCS-RS has been developed and its correct classification rate is over 90% by our experiments. In the future, the pressure distribution data of more different types of occupants will be collected, to further improve the performance of system.

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