Knowledge Acquisition Approach Based on Rough Set and Artificial Neural Network in Product Design Process

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Abstract

In this paper, product structure is taken as knowledge acquisition point, and the effective knowledge acquisition path is discussed by establishing the associated relationship between design demands of different design stages and corresponding product structure. The establishing method is to integrate rough set and artificial neural network (ANN). Design demands are reduced so as to form effective decision conditions by applying rough set. ANN model between design demands of different design stages and corresponding product structure is established to determine product structural style quickly by applying ANN, so that the needed design knowledge is acquired during design process. Finally, the general schematic design process of a roll plate machine is taken as the example to discuss the fusion application of rough set and ANN, and certify the effectivity of this method.

1. Introduction

Product design process needs designer to acquire, transform, store, apply and regenerate knowledge continually. In different design stages, designer should acquire the effective design knowledge to quickly determine corresponding product structure. So, an important problem is how to establish the effective knowledge acquisition path in design process to realize product agile development. Recently, many modern mathematics tools have been applied to acquire knowledge in product design process. Among which, rough set theory and artificial neural network (ANN) have been focused by researchers because they could commendably simulate the human thinking activities [1-4]. However, the application research of them on knowledge acquisition in design process is carried out separately. Rough set is mainly applied to knowledge reduction and extraction, but ANN is mostly applied to how to form many combining forms of product and decide the effective scheme from them. Actual design process includes two stages: one is acquisition of the effective decision knowledge, and the other is combination and choice of many product structural styles. The two stages just satisfy the advantages of rough set and ANN saperately. So, they are integrated and applied to the knowledge acquisition of design process in the paper. Rough set is taken as the front-end processing of ANN and used to extract the effective

978-0-7695-3736-8/09 $25.00 © 2009 IEEE
DOI 10.1109/ICNC.2009.415

design demands, and then the associated relationship between design demands and corresponding product structure is constructed by applying ANN. Consequently knowledge acquisition path in design process could be established and the design knowledge is acquired effectively.

2. Knowledge acquisition approach based on rough set and ANN

2.1. Using rough set theory to acquire the effective design knowledge

The aim of acquiring needed knowledge in design process is to determine product structure. However, because of the material expression form of product structure is different in different design stages, the content of the needed design knowledge is different in a degree corresponding to these different expression forms. But these knowledge is actually a kind of knowledge organizational form of different design stages. They will be finally reflected to product structure. So, acquiring design knowledge could be completely transformed into acquiring corresponding product structural style in different design stages. Design demands determine the corresponding product structural style, but the importance of these design demands is different to a degree for determining product structure. If these design demands are all taken as decision conditions, it will effect the decision process and the design efficiency. So, these design demands should be filtered by using rough set so as to eliminate redundant or unuseful knowledge and realize the knowledge reextraction [5], in which the reduced decision table of design demands is the key. The reduced decision table has the same function with the unreduced one for determining product structural style, but it includes less design demands.

2.2. Applying ANN to realize choice on multiple combining forms of product structure

The process of design demands determining product structure is essentially the multiple combinations of these modular styles and selection from them, because module combining forms of product structure maybe have many types. Especially, when there are many alternative plans in different design stages and every module has many structural styles, the possible scheme combining amounts will very huge. In these large number of combination schemes, if product structure is determined by adopting arrangement to select and judge one by one, it must will effect seriously design efficiency. ANN has unique advantage in dealing with decision problem of design scheme to realize the synthesis and induction at higher level. So, the relationship between design demands of different design stages and corresponding product structure could be established by constructing ANN model.

Back-propagation (BP) is the most popular used network model. It could realize analysis and induction of complex nonlinear problem, and give appropriate treatment for them [6]. As a result, BP network is suitable for solving those problems that have more complex internal mechanism, such as design process. In BP network model, neurons of input layer are the reduced design demands by rough set, and neurons of output layer are the corresponding product structures of different design stages, but the number of neurons in hidden layer could be accessed according to the neuronic amounts of input layer and that of output layer or empirical equation. When rough set is taken as front-end processing of neural network, it could compress information space dimension by attribute reduction on the premise of reserving important information to realize feature selection, so that training samples set of ANN is simplified.

So, knowledge acquisition path of design process based on rough set and ANN could be built up by establishing ANN model between design demands of different design stages and corresponding product structure. The establishment of knowledge acquisition path in design process is shown in Fig.1. The relation between design process and product structure could be established quickly by this path to realize rapid and effective acquisition of required design knowledge.

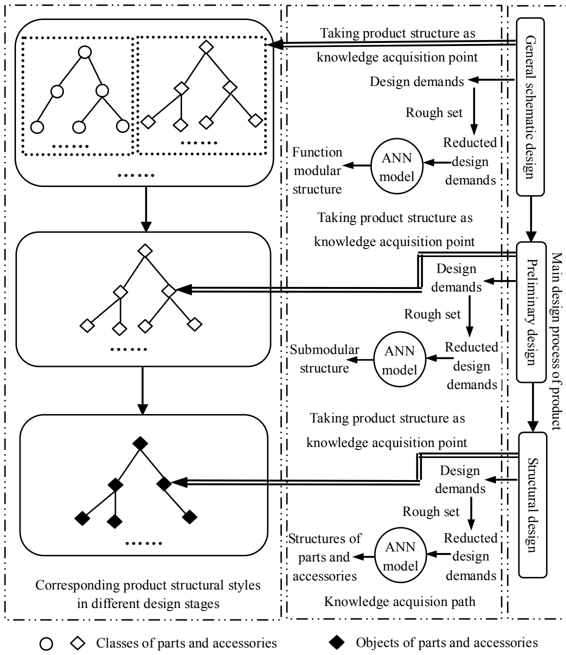

Figure 1. Knowledge acquisition path based on rough set and ANN in design process

3. Example of application

In this paper, a roll plate machine is taken as the example to discuss the establishing method of knowledge acquisition path based on rough set and ANN in the general schematic design stage.

Establishing reduced decision table by rough set theory

The design demands of a roll plate machine in the general schematic design stage include the adjustability of the roll speed, volume of the machine, thickness of the plate, width of the plate, material of the plate, line speed of the roller and the cost of the machine. In this stage, designer needs acquiring the effective knowledge to determine product structural style including transmission mode, bearing type, press equipment, driving type and type of taking plat. The samplings of design demands and that of product structural styles are shown in Tab.1 in which the value of material of the plate is expressed with its elastic ratio. In Tab.1, design demands are condition attributes and corresponding product structural styles are decision attributes. Because these property values are continuous variable, they must be discretized before reducing attributes. Constant breadth method is adopted to discretize these continuous property values in the paper, and the discretized property values are identified with italics in Tab.1.

Table 1. Property values and their discretized values in decision table

Condition attributes	Adjustability of the roll speed	Invariable	*0*	Adjustable	*1*								
	Volume of the machine	Small	*0*	Medium	*1*	Large	*2*						
	Thickness of the plate	(0~2]	*0*	(2~4]	*1*	(4~6]	*2*	(6~8]	*3*	(8~10]	*4*	(10~12]	*5*
	Width of the plate	(0~200]	(200~400]	(400~600]	(600~800]	(800~1000]	(1000~1200]	(1200~1400]	(1400~1600]	(1600~1800]	(1800~2000]		
	Width of the plate	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*		
	Material of the plate	(0~16]	*0*	(16~70]	*1*	(70~120]	*2*	(120~200]	*3*				
	Line speed of the roller	(0~100]	*0*	(100~200]	*1*	(200~300]	*2*	(300~400]	*3*				
	Cost of the machine	Low	*0*	Medium	*1*	High	*2*						
Decision attributes	Transmission mode	Bevel wheel and cycloid	*0*	Worm wheel and worm	*1*								
	Bearing type	Sliding bearing	*0*	Rolling bearing	*1*								
	Press equipment	Fluid drive	*0*	Screw equipment	*1*								
	Driving type	Direct current	*0*	Alternating current	*1*								
	Type of taking plate	Overturning	*0*	Swinging	*1*								

Table 2. Discretized decision table of 10 design examples

U/C	a_1	a_2	a_3	a_4	a_5	a_6	a_7	d_1	d_2	d_3	d_4	d_5
x_1	0	1	0	0	0	0	0	1	1	1	1	0
x_2	0	1	1	0	0	0	0	0	1	1	1	0
x_3	0	0	0	1	1	0	0	1	1	1	0	1
x_4	1	1	1	0	0	1	0	0	1	1	1	1
x_5	0	0	0	2	1	1	1	1	0	1	0	0
x_6	1	1	3	5	3	2	2	1	0	0	1	0
x_7	1	2	3	4	1	1	1	1	0	1	1	0
x_8	1	1	2	6	0	2	2	1	1	1	1	1
x_9	1	2	4	3	1	3	2	0	0	1	1	0
x_{10}	1	1	3	4	2	3	1	1	1	0	0	1

According to the result of Tab.1, 10 design examples are selected and noted respectively as x_1, x_2, $\cdots$, x_{10}.

Corresponding condition attributes are respectively noted as a_1, a_2, $\cdots$, a_7, and decision attributes are respectively noted as d_1, d_2, $\cdots$, d_5. The decision table of this 10 design examples, whose property values have been discretized, is established and shown in Tab.2. Resolution matrix *M(S)* corresponding to Tab.2 is calculated and shown in Tab.3. On this basis resolution function $f_{M(S)}$ corresponding to resolution matrix *M(S)* is calculated, and it is as following.

Table 3. Resolution matrix corresponding to Tab.2

U	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
x_1										
x_2	a_3									
x_3	a_2, a_4, a_5	a_2, a_3, a_4, a_5								
x_4	a_1, a_3, a_6	a_1, a_6	$a_1,a_2, a_3, a_4, a_5, a_6$							
x_5	a_2,a_4,a_5, a_6, a_7	$a_2,a_3, a_4, a_5, a_6, a_7$	a_4, a_6, a_7	$a_1, a_2, a_3, a_4, a_5, a_7$						
x_6	$a_1,a_3,a_4, a_5, a_6, a_7$	$a_1, a_3, a_4, a_5, a_6, a_7$	$a_1,a_2, a_3, a_4, a_5, a_6, a_7$	a_3, a_4, a_5, a_6, a_7	$a_1,a_2,a_3,a_4, a_5, a_6, a_7$					
x_7	$a_1,a_2,a_3,a_4, a_5, a_6, a_7$	$a_1, a_2, a_3, a_4, a_5, a_6, a_7$	$a_1, a_2, a_3, a_4, a_6, a_7$	a_2,a_3,a_4,a_5, a_7	a_1,a_2, a_3, a_4	a_2,a_4, a_5, a_6, a_7				
x_8	$a_1,a_3,a_4, a_5, a_6, a_7$	a_1,a_3, a_4, a_6, a_7	$a_1,a_2, a_3, a_4, a_5, a_6, a_7$	a_3,a_4,a_6, a_7	$a_1,a_2,a_3,a_4, a_5, a_6, a_7$	a_3, a_4, a_5	$a_2,a_3, a_4, a_5, a_6, a_7$			
x_9	$a_1,a_2,a_3,a_4, a_5, a_6, a_7$	$a_1,a_2, a_3, a_4, a_5, a_6, a_7$	$a_1, a_2, a_3, a_4, a_6, a_7$	$a_2, a_3, a_4, a_5, a_6, a_7$	$a_1,a_2,a_3,a_4, a_6, a_7$	a_2,a_3, a_4, a_5, a_6	a_3,a_4, a_6, a_7	a_2,a_3, a_4, a_5, a_6		
x_{10}	$a_1,a_3,a_4, a_5, a_6, a_7$	$a_1,a_3, a_4, a_5, a_6, a_7$	$a_1,a_2, a_3, a_4, a_5, a_6, a_7$	a_3, a_4, a_5, a_6, a_7	$a_1,a_2,a_3,a_4, a_5, a_6$	a_4,a_5,a_6, a_7	a_2, a_5, a_6	a_3,a_4, a_5, a_6, a_7	a_2,a_3,a_4, a_5, a_7	

$$
\begin{aligned}
&\mathrm{f}_{M(s)}(a_1,a_2,a_3,a_4,a_5,a_6,a_7) = a_3 \wedge (a_2 \vee a_4 \vee a_5) \wedge (a_1 \vee a_3 \vee a_6) \\
&\wedge (a_2 \vee a_4 \vee a_5 \vee a_6 \vee a_7) \wedge (a_1 \vee a_3 \vee a_4 \vee a_5 \vee a_6 \vee a_7) \\
&\wedge (a_1 \vee a_2 \vee a_3 \vee a_4 \vee a_5 \vee a_6 \vee a_7) \wedge (a_2 \vee a_3 \vee a_4 \vee a_5) \\
&\wedge (a_1 \vee a_5) \wedge (a_2 \vee a_3 \vee a_4 \vee a_5 \vee a_6 \vee a_7) \wedge (a_4 \vee a_6 \vee a_7) \\
&\wedge (a_1 \vee a_2 \vee a_3 \vee a_4 \vee a_5 \vee a_6) \wedge (a_1 \vee a_2 \vee a_3 \vee a_4 \vee a_6 \vee a_7) \\
&\wedge (a_1 \vee a_2 \vee a_3 \vee a_4 \vee a_5 \vee a_7) \wedge (a_3 \vee a_4 \vee a_5 \vee a_6 \vee a_7) \\
&\wedge (a_2 \vee a_3 \vee a_4 \vee a_5 \vee a_7) \wedge (a_1 \vee a_2 \vee a_3 \vee a_4) \wedge (a_3 \vee a_4 \vee a_5) \\
&\wedge (a_3 \vee a_4 \vee a_6 \vee a_7) \wedge (a_2 \vee a_5 \vee a_6) = a_3 \wedge (a_2 \vee a_4 \vee a_5) \\
&\wedge a_1 \wedge (a_4 \vee a_7) \wedge (a_3 \vee a_4 \vee a_5 \vee a_6 \vee a_7) \\
&\wedge a_2 \wedge (a_3 \vee a_4 \vee a_5) \wedge (a_3 \vee a_4) \wedge a_5 = a_1 a_2 a_3 a_4 a_5
\end{aligned}
$$

Accroding to the result of $f_{M(S)}$, the reduction of design demands could be obtained, and it is marked as red(R), that is, red(R)=$\{a_1,a_2,a_3,a_4,a_5\}$. So, condition attributes in Tab.1 have been reduced from 7 to 5. By applying rough set, the redundant attributes could be eliminated so as to realize knowledge compression and extraction. It is in favor of subsequent applying for ANN, such as reducing neuronic amounts and simplifying network configuration.

3.2. Applying BP neural network to determine product structure

The reduced condition attributes are taken as the input of ANN, and decision attributes in Tab.1 are taken as the output of ANN. BP network configuration is 5-10-5. The topological structure of this network is shown in Fig.2. ANN model is trained with MATLAB. In the training process, training function adopts BFGS quasi-Newton method, and transfer function is logsig. Learning function is learngdm, and goal error of network training sets 1e-005. 60 groups of reduced design demands are selected as the training samples, and sample data, expected outputs and output results of network training are shown in Tab.4. The values of input samples and expected output values have been normalized.

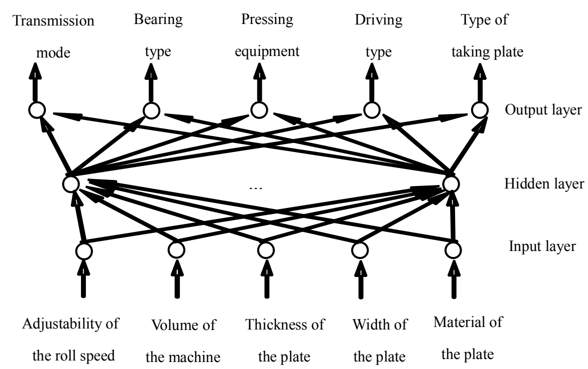

Figure 2. Topological structure of BP network

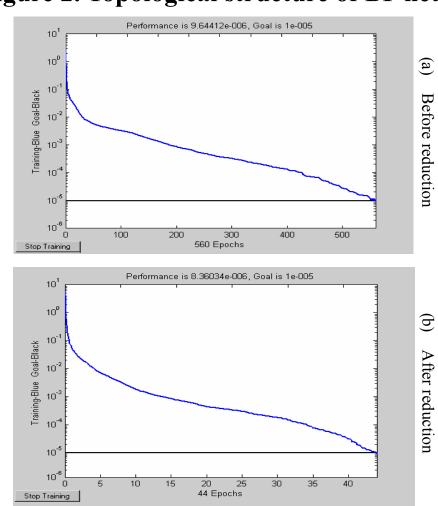

Figure 3. Training times and calculating error for reducing attributes before and after

In order to compare the influence of attributes reduction on the network training, network is retrained only by changing the neuronic amounts of input layer from 5 to 7 with same training samples. Training times and calculating error for reducing attributes before and after are shown in Fig.3. It indicates that network training speed is increased apparently, and network training time is decreased greatly after attributes have been reduced by applying rough set. Product structural styles of general schematic design stage could be determined quickly and accurately by adopting ANN method, and the relation between design demands and corresponding product structure could be established. In order to verify the generalization ability of network, new 8 groups samples are retrained with this network configuration and their values are shown in Tab.5. Calculation result indicates that network also could give the correct response for new input, that is, ANN model could forecast commendably new design task.

Table 4. Partial samples data, expected outputs and output results of network training

	Catalogue number	1	2	3	4	5	…	56	57	58	59	60
input samples	Adjustability of the roll speed	0	0	0	0	1		0	1	1	1	1
	Volume of the machine	1	0	0.5	1	0		0.5	0	0	0.5	1
	Thickness of the plate	0	0.4	0.4	0	1		0.8	1	1	1	1
	Width of the plate	0	0.111	0.222	0.555	0.444		0	0.333	0	1	1
	Material of the plate	0.293	1	1	0.293	0		0.293	0	0.293	0	1
Expected outputs	Transmission mode	1	1	1	1	0		1	1	1	1	0
	Bearing type	1	0	1	1	0		1	1	1	1	0
	Press equipment	1	0	1	0	1	…	1	1	1	1	0
	Driving type	1	1	1	1	0		1	0	0	0	0
	Type of taking plate	0	0	0	1	0		0	0	0	1	1
Output results of network training	Transmission mode	0.9809	1.0024	1.0126	1.0042	0.0032		1.0051	1.0175	1.0014	1.0027	0.0073
	Bearing type	1.0013	0.016	1.0312	0.9873	0.0057		1.006	1.0023	1.0083	1.0023	0.0153
	Press equipment	1.0102	0.0273	1.0163	0.0085	1.003		0.9896	1.007	0.9271	0.975	0.0261
	Driving type	1.0134	1.0016	1.0091	1.0022	0.0221		1.0005	0.0158	0.0035	0.0089	0.0098
	Type of taking plate	0.0253	0.0059	0.0096	0.9995	0.0016		0.0057	0.0492	0.0366	1.0027	1.0102

Table 5. Forecasting input samples, output results of network training and expected outputs

	Catalogue number	1	2	3	4	5	6	7	8
Forecasting input samples	Adjustability of the roll speed	0	0	0	0	0	0	1	1
	Volume of the machine	0	0.5	0	0.5	0	1	0.5	1
	Thickness of the plate	0.2	0	0.4	0.8	1	0.6	0.8	1
	Width of the plate	0	0.444	0.111	0.555	1	1	0	0.222
	Material of the plate	0.293	0.293	1	0	0.293	1	0.293	0.293
Output results of network training	Transmission mode	0.0182	1.0025	1.0032	0.0108	0.0986	0.0025	0.998	1.0023
	Bearing type	0.9976	1.005	1.0013	0.0206	0.068	0.0102	1.0123	1.0052
	Press equipment	1.0003	1.0053	1.0102	1.007	0.0143	0.0067	0.9916	0.989
	Driving type	0.9832	0.9987	0.9952	0.9967	1.0086	0.9912	0.0051	0.002
	Type of taking plate	0.0012	1.0105	0.0075	1.0028	0.0139	1.0092	0.0023	1.0041
Expected outputs	Transmission mode	0	1	1	0	0	0	1	1
	Bearing type	1	1	1	0	0	0	1	1
	Press equipment	1	1	1	1	0	0	1	1
	Driving type	1	1	1	1	1	1	0	0
	Type of taking plate	0	1	0	1	0	1	0	1

4. Conclusions

It is an effective path to realize knowledge acquisition in design process by integrating organically rough set theory and ANN method in the paper. Design demands are reduced by rough set so as to abstract the effective decision conditions, and on this basis ANN model is established between reduced design demands and product structure to quickly determine product structural style, and consequently, knowledge acquisition path in design process could be established. In the establishment of knowledge acquisition path, the method of integrating rough set and artificial neural network could effectively simulate designer's thought process, and it provides an effective resolvent for realizing product agile development and knowledge acquisition technique in design process.

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