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On-Line Monitoring of Grinding Status Based on Rough Set Theory*

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Abstract: This paper focuses on the new approach of on-line monitoring of grinding burn and wheel wear based on the rough set theory. This method adopts the grinding chip flow thermal signal, and acquires identification rules by establishing sensitive characteristic parameters and constructing the knowledge system through continuum attribute discretization, attribute reduction and knowledge acquisition, and then monitors grinding burn and wheel wear in accordance with the acquired rules. The experiment results show that the new method is effective.

Key words: rough sets, grinding, thermal radiation, on-line monitoring

Grinding process is always the final technological step when a workpiece is manufactured. Grinding situation directly affects the final quality of the workpieces assembled in the machine. It is one of the important subjects to monitor grinding situation on-line and to identify the burned workpieces through the monitoring and the intelligent identification method.

One of the great difficulties in on-line grinding situation monitoring is how to process the source signal for useful information so as to secure an effective method of on-line monitoring. We make full use of statistic analysis, BP neural network and self-clustering network for our research on on-line monitoring of grinding burn and wheel wear, and have reached some conclusions. There is no doubt that these approaches are effective in mass product pattern. However, as for the small batch product pattern, it is necessary to develop quite a new on-line monitoring method adapted to it. As the rough set theory is based on classification, a single sample is equal to many samples which belong to the same class. Therefore, on-line monitoring based on rough set theory is effective in the small batch product pattern.

The rough set theory is not a concept. It is formulated by Z. Pawlak in 1982, which is a set of mathematical theories for dealing with all kinds of fuzzy, imprecise and incomplete information[1]. This paper doesn't focus on the discussion of the rough set theory, but on the application of this theory to on-line monitoring of grinding situation and to the development of the method and basic steps. The basic idea is as follows: to construct knowledge symbol systems on the basis of the rough set theory, and try to find out identification rules, and then base on the acquired rules to monitor grinding burn and wheel wear. With the help of expert system for on-line modification of the rules, the system's accuracy can be improved.

1 Source Signals and Valid Characteristic Parameters

We collected grinding chip thermal flow as the signal source. The grinding chip thermal flow refers to the thermal radiation flow produced by the chips and abrasive particles spurting out from the contact zone of wheel-workpiece in the grinding process. It contains temperature information of the contact zone of wheel-workpiece and abrasive particles spurting out from the grinding wheel in the grinding process.

The scheme of the signal measurement of the grinding chip thermal flow and the system for data sampling and processing is shown in Fig.1. The infrared detector is fixed on the infeed plate. It is about 30 mm from the contact zone. There are 40 samples obtained at equal intervals in the grinding process of the outside of cylindrical parts by using a refreshed grinding wheel. The grinding chip thermal flow signal is sent to the computer via the A/D sampling card.

As grinding chip thermal flow signal is stochastic, it is difficult to identify grinding burn and wheel wear directly. So it is necessary to find an effective method to process the signal for valid characteristic parameters. Through experiments and feature analysis,

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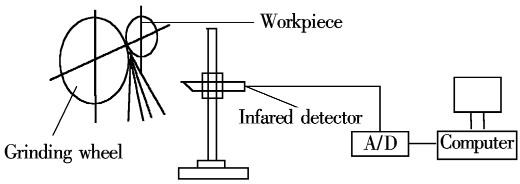

Fig.1 A scheme of experiment arrangement

we have acquired four variables as valid characteristic parameters: the sample mean and variance of the grinding chip flow signal, the autoregression coefficient φ_1 and φ_2 of AR(2) model based on system distinguishing[2-4]. To save space, this paper will not discuss why to take these four variables as valid characteristic parameters.

2 Knowledge Express System

In developing the on-line monitoring expert system of grinding burn and wheel wear, the grinding burn and wheel wear field knowledge is required and should be expressed through symbols (and also usually through differentiate rules). Knowledge is linked to classification in the rough set theory and considered to be a kind of classifying ability based on objects. Knowledge consists of classification modes of interested object sets, including obvious truths of the objects as well as the ability of deducing concealed truths from obvious truths. The basic part of the knowledge express system is sets of objects. The information of the objects is described with the basic features (attributes) and their characteristic values (attribute values). A knowledge express system S can be showed as follows:

$$S = (U, C, D, V, f)$$

where U is a finite non-null set of objects, called discussing field, which includes diagnosis examples of all workpieces in the course of grinding. $C \cup D = A$ is a set of attributes, and son set C and D are a set of condition attributes and decision attributes, respectively. C corresponds with characteristic parameters which identify grinding faults. We choose the sample mean and standard deviation of the grinding chip flow signal and the autoregression coefficient φ_1 and φ_2 of AR(2) model based on system distinguishing as condition attributes C_1, C_2, C_3, C_4. Decision attribute D corresponds to grinding situation, value $d = 1$ represents normal state, $d = 2$ is wheel wear and $d = 3$ is grinding burn. $V = \bigcup_{a \in A} V_a$ is a set of the attribute value, V_a is the land of the attribute value, corresponding to C_1, C_2, C_3, C_4 and d values of each examined workpiece sample. $f: U \times A \rightarrow V$ is an information function, which decides the attribute values of each object x of U on the attribute set a. It corresponds with the inherent law that determines the concrete parameters of each workpiece sample, which is just the rule that we want to acquire. The knowledge express system can be easily realized with the decision table. In the decision table of the knowledge express system, rows denote attributes and lines denote objects, and each line expresses the information of the corresponding object. The decision table of the part of 10 workpieces examined in our laboratory is shown in Tab.1.

Tab.1 Continuum attributes decision table of grinding fault distinguishing system

Number of workpiece	C_1	C_2	C_3	C_4	d
1	-3.165×10^{-5}	0.016 386 33	0.079 663	0.279 668	1
2	-4.359×10^{-5}	0.014 218 20	−0.060 495	0.192 477	1
⋮	⋮	⋮	⋮	⋮	⋮
10	6.618×10^{-5}	0.031 139 54	0.225 354	0.324 858	3

3 Continuum Attribute Discretization

As the knowledge in the expert system includes mostly the human expert's experience hard to quantify, and it is usually expressed with abstract logic symbols, the expert system based on the knowledge can only handle discrete information. Therefore, the continuum attribute in the information system must be converted into the discrete attribute. That is, to divide the continuum attribute value land into several blocks, with each block expressed with different codes. As a result, the continuum attribute value is converted into discrete attribute.

There are two discretization methods: non-relevant discretization and relevant discretization. Relevant discretization deals with the corresponding relation of condition attributes and decision attribute, and the distribution on decision attribute determines the discrete blocks. However, non-relevant discretization handles only condition attributes, and is of wanton quality, so the discretization result is often unsatisfactory.

Because an unreasonable wanton discretization leads to the worsening of the study performance in the rough set theory, the acquired rules do not conform to practical application. To improve the study performance, continuum attribute discretization must be compatible with the inducing study method. The inducing study method establishes condition attributes and decision attribute corresponding relations, so continuum discretization must consider the corresponding relation of condition attributes and decision attribute as well. As the condition attributes of undergoing discretization like this include more classified information, and it can possibly reflect the corresponding relation between condition and decision attributes with less condition attributes, so it is likely to reduce the knowledge express system.

It is necessary to adopt relevant discretization in the intelligent diagnosing system based on the rough set theory. With the criterion of Shannon entropy and FUSINTER discretization[5], the discretization points of Tab.1 are acquired as follows.

The discretization point of the sample mean of the grinding chip flow signal is 5.323×10^{-5}, the standard deviation of the grinding chip flow signal is 0.027 3, the autoregression coefficient φ_1 of AR(2) model is 0.253 3, and the autoregression coefficient φ_2 of AR(2) model is 0.230 9.

The discrete attribute values are set 2 when their continuum attribute values are greater than the discretization points, and the discrete attribute values set 1 when their continuum attribute values are smaller than the discretization points. Through the relevant discretization and continuum attribute decision table of the grinding fault distinguishing system (See Tab.1) is converted into the discrete attribute decision table of the same system (See Tab.2).

Tab.2 The discrete attribute decision table of grinding fault distinguishing system

Number of workpiece	C_1	C_2	C_3	C_4	d
1	1	1	1	2	1
2	1	1	1	1	1
3	1	1	1	2	1
4	1	1	1	1	1
5	1	1	1	1	1
6	1	1	2	1	1
7	1	2	2	2	1
8	2	2	2	2	3
9	1	2	2	2	2
10	2	2	1	2	3

4 Group Classification Modes

In Tab.2, the objects 1 and 3 have the same attribute values, the objects 2, 4 and 5 have another the same attribute values, and they can be grouped as two samples according to the rough set theory. Next, we will show why the same samples can be grouped as one sample without affecting the acquired rules.

For convenience in mathematic calculation, the rough set theory uses equivalent relation to replace classification. A classification of U is the same as an equivalent relation of U. The two can replace each other. As we know, the equivalent relation is easy to handle. Knowledge can be interpreted as using the equivalent relation clan $\boldsymbol{R}$ to divide the discrete space, and the result right to divide is knowledge. Then the knowledge express system can be interpreted as a relation system $K = (U, \boldsymbol{R})$. Here, U is the discussing field, and $\boldsymbol{R}$ is the equivalent relation clan of U.

An equivalent relation $R \in \boldsymbol{R}$ is equal to the classification of one dimension space R of the discussing field. If R is one equivalent relation of U, $U/R = \{X_1, X_2, \cdots, X_n\}$ is an equivalent relation clan for relation R to divide U. $[x]_R = \{y \in U \mid xRy\}$ is the equivalent class including element x.

If the sub set $\boldsymbol{P} \subseteq \boldsymbol{R}$ and $\boldsymbol{P} \neq \varnothing$, $\bigcap \boldsymbol{P}$ is the classification in multidimensional space P of U, called $\mathrm{IND}(\boldsymbol{P})$. It is one equivalent relation too, called an undividable relation. $U/\mathrm{IND}(\boldsymbol{P})$ is the classification of $\mathrm{IND}(\boldsymbol{P})$ of U, simplifying it as $U/\boldsymbol{P}$.

Suppose there are two knowledge systems $K = (U, \boldsymbol{P})$ and $K' = (U, \boldsymbol{Q})$. If $\mathrm{IND}(\boldsymbol{P}) = \mathrm{IND}(\boldsymbol{Q})$, K is equal to K'. If $\mathrm{IND}(\boldsymbol{P}) \subset \mathrm{IND}(\boldsymbol{Q})$, knowledge $\boldsymbol{P}$ is more detailed than knowledge $\boldsymbol{Q}$, and is the melting specially of knowledge $\boldsymbol{Q}$, which is the popularization of knowledge $\boldsymbol{P}$. The knowledge and the classification are closely linked. Classes resulting from classification are the module which forms knowledge, and basic classes $U/\boldsymbol{P}$ from undividable relations form the basic module. The equivalence, melting, popularizing of the knowledge are compared with the basic classes. Equivalence means that basic classes of the two knowledges are identical, and popularizing is to associate some basic classes, and specializing is to separate the basic classes for smaller units.

In the fault diagnosing system, the equivalent relation clan $\boldsymbol{P}$ represents the symptom and $\boldsymbol{Q}$ represents the faults. Each diagnosis example is treated as one object, and all diagnosis examples form the discussing field. If $\mathrm{IND}(\boldsymbol{P}) \subset \mathrm{IND}(\boldsymbol{Q})$, the basic classes of the knowledge system $K' = (U, \boldsymbol{Q})$ include all basic classes of the knowledge system $K = (U, \boldsymbol{P})$. Knowledge $\boldsymbol{P}$ offers redundant classification ability, so it can be popularized. Namely, when $\mathrm{IND}(\boldsymbol{P}) = \mathrm{IND}(\boldsymbol{Q})$, it can group the basic classes of $K = (U, \boldsymbol{P})$. Therefore, the samples with the same condition attribute value and decision attribute value can be grouped as one.

Additionally, if $\mathrm{IND}(\boldsymbol{Q}) \subset \mathrm{IND}(\boldsymbol{P})$, it shows that the classification ability that knowledge $\boldsymbol{P}$ offers is insufficient, and it cannot make an effective diagnosis.

In this case, supplementary new symptoms are needed or lower the requirement for the precision of diagnosing, namely to segment the basic classes of the knowledge system $K = (U, \boldsymbol{P})$ or to group the basic classes of the system $K' = (U, \boldsymbol{Q})$.

In terms of the above-mentioned theory, the discrete attribute decision table of the grinding fault distinguishing system can be converted into decision table (see Tab.3), which includes only classification modes, where each line represents a class, but not a sample. The inducing study method of the rough set theory cares only about the classification of condition or decision attributes, but is insensitive to the number of samples. Therefore, it is not hard to see that the study method based on the rough set theory has the following merits:

a) Effective in solving the small sample problem and the sample maldistribution problem. One classification mode may include a large number of samples, or only a few samples, and the number of different modes may also vary greatly. So long as there is only one sample of classification in the discussing field, the study method can acquire knowledge.

b) Capable of reducing the complexity of calculation greatly. As the number of the training samples is generally far beyond that of the classification modes, the calculating operation is unimaginably complex and demanding. This method can reduce the system resource taken up and save a lot of time by grouping the classification modes before attribute reduction or knowledge acquisition.

Tab.3 Decision table based on classification modes

Classification	C_1	C_2	C_3	C_4	d
1	1	1	1	2	1
2	1	1	1	1	1
3	1	1	2	1	1
4	1	2	2	2	1
5	1	2	2	2	2
6	2	2	1	2	3
7	2	2	2	2	3

5 Attribute Reduction

To reduce the negative effect of data disorder and redundancy, it is necessary to remove redundant information that has nothing to do or has relatively little dependence with the study goal. That is the process of attribute reduction, which aims to delete redundant attributes without losing the classification ability. According to the decision table definition that the rows of the table are attributes and the lines are objects, attribute reduction is to delete redundant attribute rows in the table. In this paper, the methods of difference matrix and difference function are applied to the logic reduction.

In the information system $S = (U, C, D, V, f)$, $A = C \cup D$, $n \times n$ difference matrix of attribute sets $B \subseteq A$ is defined as follows:

$$\delta(x, y) = \{a \in B : a(x) \neq a(y)\} \quad x, y \in U$$

Obviously, the difference matrix is a symmetry matrix. In order to calculate D set reduction of C set, the above-mentioned difference matrix is redefined as follows (called (C, D) difference matrix, and marked as $M(C, D)$):

$$\delta(x, y) = \begin{cases} \{a \in C : a(x) \neq a(y)\} & [x]_D \neq [y]_D \\ \varnothing & [x]_D = [y]_D \end{cases}$$

According to difference matrix definition, if attribute sub set $R \subseteq C$, difference matrix $M(R, D)$ of information system $S' = (U, R, D, V, f)$ and difference matrix $M(C, D)$ of information system $S = (U, C, D, V, f)$ has the following relation:

$$M(R, D) = M(C, D) \cap R = (\delta(x, y) \cap R)_{n \times n}$$

Difference matrix $M(C, D)$ has only confirmed a difference function $f_D(C)$, defined as:

$$f_D(C) = \prod_{(x,y) \in U^2} \left\{ \sum \delta(x, y) : (x, y) \in U^2 \text{ and } \delta(x, y) \neq \varnothing \right\}$$

where $\sum \delta(x, y)$ is Boolean operation of variables of all attributes of attribute set $\delta(x, y)$. $f_D(C)$ is a Boolean function. The extract model pattern of $f_D(C)$ can be acquired by using the distribution law and absorb law in Boolean algebra. All conjunction items of the minimum extract model pattern of $f_D(C)$ are D set reduction of all corresponding C sets.

According to the above-mentioned theory, Tab.3 can be converted into the decision table of the minimum attributes (See Tab.4).

Tab.4 The decision table of the minimum attributes

Classification	C_1	C_2	d
1	1	1	1
2	1	1	1
3	1	1	1
4	1	2	1
5	1	2	2
6	2	2	3
7	2	2	3

The decision table of the minimum attributes and the primitive decision table have self-same classification decision ability, and they divide the discussing field same, but the decision table of the minimum attributes contains far fewer condition attributes than the primitive decision table. The key feature of the information system can be found through attribute reduction. The lesser of the number of attributesis, the stronger the expansion ability of knowledge is. It guarantees the efficiency of knowledge acquisition through the inducing study method.

6 Knowledge Acquisition

After attribute reduction, we may move on to knowledge acquisition, namely to obtain the production type rules with inclusive knowledge from the expert system by studying with the simplest knowledge express system. The rules include the determinate and the possible ones.

In the information system $S = (U, C, D, V, f)$, $\forall x \in U$, x determines only the basic formula of C and the basic formula of D, respectively marked as $\mathrm{des}_C(x)$ and $\mathrm{des}_D(x)$:

$$\mathrm{des}_C(x) = \bigwedge_{c \in C} (c, c(x))$$

$$\mathrm{des}_D(x) = \bigwedge_{d \in D} (d, d(x))$$

Each object x of the information system S has the corresponding decision rule r_x^C. It can be expressed with the basic formula of C and the basic formula of D:

$$r_x^C : \mathrm{des}_C(x) \to \mathrm{des}_D(x)$$

where $\mathrm{des}_C(x)$ is called the condition part of rule r_x^C, and $\mathrm{des}_D(x)$ is called the decision part. If $|\mathrm{des}_C(x)|_S \subseteq |\mathrm{des}_D(x)|_S$; namely $\mathrm{des}_D(x)$ depends on $\mathrm{des}_C(x)$ totally, and r_x^C is determinate rule. Otherwise, r_x^C is possible rule.

If r_x^C is determinate rule, $r_x^C : \mathrm{des}_C(x) \xrightarrow{D} \mathrm{des}_D(x)$.

If r_x^C is possible rule, $r_x^C : \mathrm{des}_C(x) \xrightarrow{P} \mathrm{des}_D(x)$.

In the rough set theory, the decision classes intersecting with other decision classes in decision space are called rough classes. It can be expressed with low approach and high approach. Knowledge acquisition can induce the determinate rules or the possible rules according to low approach and high approach of certain decision classes. If the primitive decision table includes k decision classes, i.e. k decision attribute values, and each decision class produces two divisions, there are $2k$ new division classes produced on U, called substitute division classes. Each substitute division class can be divided into two sub sets, one of which is low approach or high approach of this decision class and the other is the benefit set of the first set on U. The classification acquired by low approach is called low substitute division classes, and the classification acquired by high approach is called great substitute division classes. The decisions corresponding with low or high substitute division classes are called low or high substitute decisions.

The determinate rule set of decision class X corresponds with low substitute division classes, and the possible rule set of decision class X corresponds with high substitute division classes. By calculating, the most reductive determinate rule set of Tab.4 is as follows:

$(c_2, 1) \to (d, 1)$

$(c_1, 2) \to (d, 3)$

The most reductive possible rule set of Tab.4 is

$(c_1, 1) \wedge (c_2, 2) \to (d, 1)$

$(c_1, 1) \wedge (c_2, 2) \to (d, 2)$

With the help of the above-mentioned deduction, we can acquire the determinate rules of on-line monitoring of grinding burn and wheel wear as: if the sample variance is small, the grinding state is normal; if the sample mean is big, the grinding state is grinding burn. The possible rules are: if the sample mean is small and the sample variance is big, then the grinding state is possible wheel wear. The rules can be stored in the relation database system of the expert system, and the rules in the expert system can be appended, obliterated and updated so as to improve the identifying precision. The expert system can use these rules to identify the grinding state.

In the end, by combining the acquired rules with the expert system and through regular updating adding, deleting and arranging, the online discerning of the state of paring can be realized.

7 Experiment Results and Conclusions

The system generates the results from the data (See Tab.5).

Tab.5 Identifying result and experiment result

	Experimental result		Identifying result	
	Number	Sample serial number	Number	Sample serial number
Normal	21	1 – 12, 14 – 19, 37 – 39	21	1 – 12, 14 – 19, 37 – 39
Wear	14	21 – 23, 25 – 35	14	21 – 23, 25 – 35
Burn	5	13, 20, 24, 36, 40	6	13, 19, 20, 24, 36, 40

Tab.5 shows that the results are concordant with practical situation except that No.19 is on the border of burn and normal area, which does verify the feasibility of on-line monitoring of grinding burn and wheel wear on the basis of the rough set theory.

In conclusion, the induction learning method originating from the rough set theory works well in the small batch product pattern, because the theory is based on classification and therefore a single sample may equal a number of samples of the same class. So there is no doubt that it is feasible to monitor on-line grinding burn and wheel wear based on the rough set theory. This method may also apply to many other relative fields.

However, our research is only at experimental stage. The source sample and characteristic parameters are not universal, and the classes are so few that the acquired rules are limited as well. This method, though effective in research, is still not suitable for direct practical application. Now, we are cooperating with some lathe factories to improve the system. The result of the cooperation, we believe, will be the development of a highly effective and practical on-line monitoring system for detecting grinding bun and wheel wear.

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基于粗糙集理论的磨削状态在线监测

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摘　要　本文着重研究了基于粗糙集理论的在线辨识磨削烧伤和砂轮磨钝的新方法,以测取信号、计算敏感特征量、构造辨识砂轮磨损和磨削烧伤的知识表示系统、连续属性离散、分类模式的合并、属性约简、知识提取的顺序对获取的信息进行处理,提取判别规则,进而通过判别规则来辨识磨削烧伤和砂轮磨钝.经实验室试验,本方法的辨识结果与试验数据相符.

关键词　粗糙集, 磨削, 热辐射, 在线检测

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