Research Article
Fault Diagnosis of Machine Tool Based on Rough Set

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Abstract: Fault diagnosis of machine tool plays an important role on advanced manufacturing. The correct and rapid identification of faults depends on diverse sensing data and reasonable knowledge intensively. In this paper, a method based rough set is applied to diagnose faults of machine tool during the processing and a rapid fault diagnosis system based on rough set is also proposed. The approach correctly extracts diagnosis knowledge from the data that are obtained from both sensors and inspection devices and then generates a set of minimal diagnostic rules which could be used to quickly determine the failures of mechanical process, combined with data. Furthermore an actual instance is presented to illustrate the efficiency of the method in the end.

Keywords: Fault diagnosis, knowledge, machine tool, rough set

INTRODUCTION

The CNC machine tool is the widely used in manufacturing system. CNC machine tool failure is the main reason for the degrading of part quality. However, the complexity of the CNC machine tool results the challenge of fault diagnosis. There are many fault sources such as electrical system, tool system and hydraulic system and so on. Therefore, the study of fault detection and diagnosis is the crucial topic of design and operation of CNC machine tool.

The fault diagnosis of CNC machine tool refers to detect the unqualified part and the abnormal signal of machine tool processing. Significant research can be found on the fault detection of machine tool based on the fault signal process. Bing et al. (2012) introduced an adaptive stochastic resonance signal processing technique to extract the fault feature of machine tool. Compared the fast fourier transform, this method is better to detect the fault characterization. Tony and Ming (2011) presented a diagnosis technique to detect and diagnose the mechanical faults based on the discrete hidden Markov model and validated in tool wear/fracture and bearing faults scenarios. Zhao et al. (2011) proposed a fault diagnosis method of the rotary axis of a computer numerical control machine tool based on the servo motor current analysis and an ensemble empirical mode decomposition method is used as a self-adaptive low-pass filter to extract valuable information from the current signal.

The above methodologies have great results, which critical step is analyses the signal then extract the fault characteristic. Artificial intelligent technique is another technique to solve knowledge discovery such as Rough Set, neural network and so on.

Rough set is a powerful tool in fault diagnosis area. The advantage of Rough set is that is neither needs additional information about the data, nor is it necessary to correct the inconsistencies manifested in data (Xie et al., 2010; Pawlak and Skowron, 2007). Khoo et al. (2001) proposed a novel approach based on rough set theory and a pairwise comparison table for fault diagnosis and attempted to learn from the pattern of decision-making by domain experts from past experience. Mannar and Ceglarek (2004) presented a machine learning approach to fault diagnosis based on rough sets, which is able to detect hidden patterns from data leading to their resolution and applied in an assembly process of part. However, how to diagnose faults in machine tool based on the sensor signals and dimension fluctuation of part has not been investigated.

STRUCTURE OF FAULT DIAGNOSIS OF MACHINE TOOL

Rough set-based fault diagnosis knowledge acquisition is the core subsystem of the fault diagnosis of machine tool. The system includes data acquisition, knowledge discover based on rough set, machine, database and knowledge base, which are shown in the
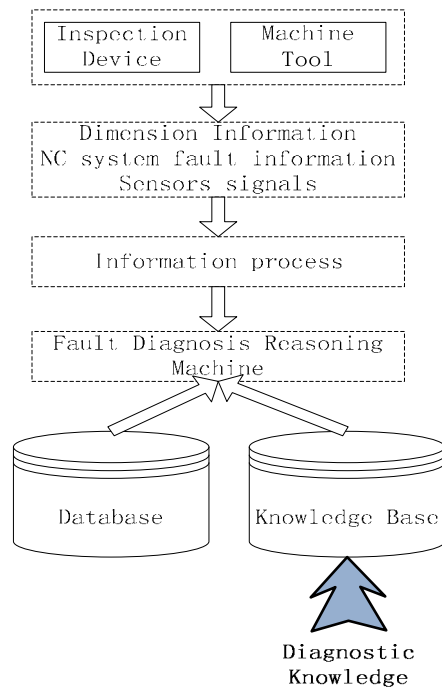
Fig. 1.

Fig. 1: Fault diagnosis system structure

- **Data acquisition:** the monitoring sensors include the press of hydraulic system, the temperature of hydraulic oil and the current of spindle, which installed in the machine tool. The NC system also provides the alarm and fault information of the machine tool. The inspection device measures the diameter of the hole and the straightness of hole. The measurement data save in the database.
- **Knowledge discover based on rough set:** the rules of the fault diagnosis are discovered using rough set. The signals of sensors, the dimension of parts and the information of NC system are the input information of this module.
- **Machine:** the machine enables to explore situation which includes both the control and simulate the experience.
- **Database and knowledge base:** the inputs data are saved in the database and the rules of knowledge discover are saved in the knowledge base. The rules are added with the increase of cases.

MODULE OF KNOWLEDGE DISCOVERING BASED ON ROUGH SET

Rough set presents a powerful tool for data analysis and discovering from imprecise and incomplete information. The hidden relationship of the system may be discovered and expressed in the form of decision rules based on the lower and upper approximations in rough set. Rough set method can be applied as component of solutions in machine learning and data mining. The research goal of rough set is an information system $S = (U, A, V, f)$, where $U = \{x_1, x_2, ..., x_n\}$ is a finite set of objects, which in this case are states of environment, A is a finite set of attribute, and the attributes in A are further classified into two disjoint subsets, condition attributes C and decision attributes D, such that $A = C \cup D$ and $C \cap D = \emptyset$; $V = \bigcup_{a \in A} V_a$ is a set of attribute values and V_a is a domain of attribute a; $f: U \times A \rightarrow V$ is an information function that assigns particular values from domains of attributes to objects such that $f(x_i, a) \in V_a$, for all $x_i \in U$ and $a \in A$. Every object that belongs to U is associated with a set of values corresponding to the condition attributes C and decision attributes D.

According to Fig. 1, rough set is applied to the fault diagnosis system of machine tool, and the rules of fault diagnosis knowledge of machine tool is defined as $S = (U, A, V, f)$. The set of condition attributes C represents the signals of sensors, the dimension of parts and the information of NC system, and the set of decision attributes D is the set of knowledge of fault reason which could have several values.

The failure object set is presented to A, $\frac{U}{R_A} = \{[x]_A : x \in R_A\}$ or $\frac{U}{R_D} = \{[x]_D : x \in R_D\}$, where $R_A = \{(x_i, x_j) : f_a(x_i) = f_a(x_j)(a \in A)\}$; $R_D = \{(x_i, x_j) : f_d(x_i) = f_d(x_j)(d \in D)\}$ are called indiscernibility relationship decided by A. For any $B \subset A$, an equal value relation can be obtained, $R_B = \{(x_i, x_j) : f_a(x_i) = f_a(x_j)(a \in B)\}$, and one partition is then acquired U/R_B, namely, $[x]_B = \{y : (x, y) \in R_B\}$ (Liu, 2001; Xie *et al.*, 2010)

The decision set is the group of fault decision knowledge, which is presented using rules that is generated by the knowledge reduction. Moreover, it is a process that identifies decision knowledge class and completes knowledge acquisition of the fault diagnosis knowledge.

EXPERIMENTAL RESULTS

The NC machine tool is widely applied in manufactory, which has high process accuracy and reliability. So, the complex part is processed using the NC machine tool. Besides the error information from the NC system, the sensors are also installed in the machine tool to inspect the process. After the process, the inspection device detect the processing size to determine whether the size beyond the tolerance. A shaft part is taken for example.

Table 1: Fault diagnosis decision system

U	a_1	a_2	a_3	a_4	a_5	a_6	D
1	1	0	1	1	0	0	d_3
2	0	0	1	1	0	0	d_3
3	0	1	0	1	1	0	d_1
4	1	0	0	0	1	1	d_1
5	1	0	0	0	0	0	d_2
6	0	1	0	0	0	0	d_2
7	1	0	0	1	1	1	d_3
8	0	0	1	0	0	1	d_3
9	1	0	1	0	1	0	d_1

Table 2: Decision table after reduction

U	a_1	a_3	a_4	a_5	D
1	1	1	1	0	3
2	0	1	1	0	3
3	0	0	1	1	1
4	1	0	0	1	1
5	1	0	0	0	2
6	0	0	0	0	2
7	1	0	1	1	3
8	0	1	0	0	3
9	1	1	0	1	1

Data acquisition: A shaft part is processed using a NC lathe and a stepped hole in the part. The input information of rough set knowledge discovering module are as follows:

- The diameter of hole is over tolerance
- The straightness of hole is over tolerance
- The temperature of hydraulic oil is too high
- The press of hydraulic oil is too large
- The current of spindle is too large
- The errors from the NC system

The knowledge discovering module can analyze the aforementioned input data and extract the fault diagnosis rules.

Formation and discretion of the sample of knowledge acquisition: After the rough set module obtains the data, the continuous value should be discretization. The condition attributes are $a_1 \sim a_6$, namely, the diameter of inner hole is more than the allowance above-nominal size, the diameter of inner hole is less than allowance below-nominal size, the straightness is more than the allowance above-nominal size, the press of hydraulic system is too high, the current of main spindle is extremely increased, the alarm from the NC system. The attribute value that equals to 1 means the characteristic exists, and 0 means that it does not exist. D, represented as the decision attribute, means the sort of fault. The value of 0 represents error of the tool system, 1 represents co-ordination fault of the spindle and the spindle hole, 2 represents the transmission system failure. After

discretization, the condition attributes and decision attribute constitute a 2D table, which each row represents a practical fault diagnosis object and each column represents one attribute. The table is shown in the Table 1.

Reduction computation of decision table: The reduction computation operation is to delete the attributes what have little influence on the final fault diagnosis decision. The reduction operation includes the conditional attribute reduction (delete redundant column) and attributes value reduction (delete redundant attribute value in decision table). The minimal decision table is constructed after reduction.

Conditional attribute reduction: The discernibility matrix is adopted to reduce attributes (Pawlak and Skowron, 2007; Xie *et al.*, 2010). The matrix reduction steps are as follows:

- Compute the discernibility matrix $M(S)$. The discernibility $M(S)$ is a symmetric $n \times n$ matrix with entries $= \{a \in A : a(u_i) \neq a(u_j) \land u_j, u_i \in U i,j=1,\cdots n$; then, each entry includes the set of attributes on u_i and u_j.

- Calculate the discernability function $f_{M(S)}$. $f_{M(S)}$ is a Boolean function of $a_1^*, \cdots, a_m^*$ defined as follows: $f_A(a_1^*, \cdots, a_m^*) = \{\lor c_{ij}^* | 1 \leq j \leq i \leq n, cij \neq \emptyset$, where $cij* = a*a \in cij$. In the fault diagnosis system, the $f_{M(S)}(a_1, a_2, a_3, a_4, a_5, a_6) = (a_1 \lor a_2) \land a_3 \land a_4 \land (a_5 \lor a_6)$.

- Compute the minimal disjunctive normal form. The attributes $\{a_1, a_3, a_4, a_5\}$ is adopted; and the reduced decision table is shown in Table 2. One decision rule is generated based on one row in Table 2.

Attribute value reduction After the column reduction, the attribute value reduction table is generated. Take the computation of attribute value reduction of decision rule 1 for example. Let $F = \{[1]_{a1}, [1]_{a3}, [1]_{a4} [1]_{a5}\}$, and all subset $\theta \subseteq F$ should be computed to get the reduction F. $[1]_{a1} = \{1,4,5,7,9\} \not\subset [1]_D$, $[1]_{a3} = \{1,2,8,9\} \not\subset [1]_D, [1]_{a4} = \{1,2,3,7\} \not\subset [1]_D$ and $[1]_{a5} = \{3,4,7,9\} \not\subset [1]_D$, and so on. The set of $[1]_{a1a4} = \{1,7\} \subset [1]_D$, $[1]_{a3a4} = \{1,2\} \subset [1]_D$, $[1]_{a3a5} = \{1,2,8\} \not\subset [1]_D$, and $[1]_{a4a5} = \{1,2\} \not\subset [1]_D$. Thus, the reduction of decision rule 1 is $a_1 a_4 \rightarrow D_1$, $a_3 a_4 \rightarrow D_1$, $a_3 a_5 \rightarrow D_1$ and $a_4 a_5 \rightarrow D_1$. In accordance with this method, the attribute value reduction table is Table 3.

Table 3: Attribute value reduction

U	a_1	a_3	a_4	a_5	D
1	1	–	1	–	3
1'	–	1	1	–	3
1"	–	1	–	0	3
1'''	–	–	1	0	3
2	0	1	–	–	3
2'	–	1	1	–	3
2"	–	1	–	0	3
2'''	–	–	1	0	3
3	0	–	–	1	1
4	–	–	0	1	1
5	–	0	–	0	2
6	–	0	–	0	2
7	1	–	1	–	3
8	0	1	–	–	3
8'	–	1	–	0	3
9	–	1	–	1	1
9'	–	–	0	1	1

Table 4: One minimal decision rule table

U	a_1	a_3	a_4	a_5	D
1	1	–	1	–	3
2	–	1	1	–	3
3	–	1	–	0	3
4	–	–	1	0	3
5	0	1	–	–	3
6	0	–	–	1	1
7	–	–	1	1	1
8	–	0	–	0	2
9	–	1	–	1	1

Formation of minimal decision rule table: After combining and selecting decision rules, 1-9, one minimal decision rule table is shown as Table 4.

FORMATION OF FAULT DIAGNOSIS KNOWLEDGE REPRESENTATION

After the minimal decision rule table is generated, the fault diagnosis rule is represented in "if-then" form, namely, if$(p_1, p_2, \cdots, p_m)$, then$(q_1, q_2, \cdots, q_n)$, where $p_1, p_2, \cdots, p_m$ represents the conditional attributes in diagnosis rule; $q_1, q_2, \cdots, q_n$ represents the corresponding decision attributes. The description of the first row of table 4 is as follows:

If the diameter of inner hole is larger than the allowance above nominal size and the temperature of hydraulic oil is increased then the transmission system of machine tool has a fault.

All fault diagnosis rules are generated according the Table 4, then inputted into the knowledge base of fault diagnosis system of machine tool.

CONCLUSION

In this study, a rule generation method based on rough set is presented and an application of machine tool is given. The results have validated the effectiveness of using rough set for fault diagnosis. The product quality of machine tool can be improved using the fault diagnosis system and then the production line achieves higher economic benefits.

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