Application of fuzzy logic and variable precision rough set approach in a remote monitoring manufacturing process for diagnosis rule induction

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Rough set has been shown to be a valuable approach to mine rules from a remote monitoring manufacturing process. In this research, an application of the fuzzy set theory with the fuzzy variable precision rough set approach for mining the causal relationship rules from the database of a remote monitoring manufacturing process is presented. The membership function in the fuzzy set theory is used to transfer the data entries into fuzzy sets, and the fuzzy variable precision rough set approach is applied to extract rules from the fuzzy sets. It is found that the induced rules are identical to the practical knowledge and fault diagnosis thinking of human operators. The induced rules are then compared with the rules induced by the original rough set approach. The comparison shows that the rules induced by the fuzzy rough set are expressed in linguistic forms, and are evaluated by plausibility and future effectiveness measures. The fuzzy rough set approach, being less sensitive to noisy data, induces better rules than the original rough set approach.

Keywords: Fuzzy sets, rough sets, data mining, remote monitoring, E-maintenance

1. Introduction

With the development of information technology, computer networks, and computational intelligence, modern manufacturing processes and equipment have become more intelligent and complex than before. As a result it becomes more difficult to diagnose and maintain this kind of process or equipment when it has problems.

Traditionally, when a problem occurs in a customer’s machine, it is reported to the hot-line service center that is set up to answer the frequently encountered problems from customers. A service engineer will then suggest a series of checkpoints. Such suggestions are based on past experience. If the problem is not resolved in this stage, the service center will despatch a service engineer to the shop floor of the customer for an on-site repair. Usually, this is a time-consuming and cost ineffective maintenance process.

Since the modern machine is equipped with advanced data collection systems and is monitored real time, the manufacturing database of this machine stores huge valuable data that offer promising opportunities for shortening the machine fault diagnosis and maintenance process. If proper data mining techniques are applied to this database, some potential cause-and-effect rules may be extracted to facilitate the machine fault and diagnosis process. The extracted rules may provide more promising results in diagnosing manufacturing process faults than the pure human experience.
Hou et al. (2003) have developed an integrated system for the intelligent remote monitoring and diagnosis of a manufacturing process. In this system, a back propagation neural network is used to monitor the manufacturing process and to identify faulty quality categories of the product being produced, and the rough set based data-mining system is applied to extract the causal relationship between manufacturing parameters and product quality measures. The integration of neural networks and a rough set approach not only provides information about what is expected to happen but also reveals why this has occurred and how to recover from the abnormal condition with specific guidelines on process parameters setting.

Hou et al. (2003) have applied this system to a real industrial case and demonstrated the robust effectiveness of the system. However, the data entries in the manufacturing database have quantitative variations, and these variations have the form of linguistic expressions. They suggest that fuzzy sets may be integrated with the rough set approach to extract rules. Therefore, the objective of this research is to integrate fuzzy sets with rough sets to induce rules from the database of a remote monitoring manufacturing process. The membership function in the fuzzy set theory is used to transfer the data entries in the manufacturing database into fuzzy sets, and then the fuzzy variable precision rough set approach is applied to induce rules from the fuzzy sets. Finally, the proposed system is applied to the same example used by Hou et al. (2003) to extract rules that are then compared with those of Hou et al. (2003) and conclusions are drawn based on this comparison.

2. Fuzzy set and rough set theories

2.1. Fuzzy set theory

Fuzzy set theory is primarily concerned with quantifying and reasoning using linguistic expression in which words can have ambiguous meaning (Zadeh, 1988). If a set of \( X \) is a collection of objects \( x \) (e.g., stature of students), and \( A \) is a fuzzy set (e.g., high), then an element of the universe (i.e., \( x \)) that belongs to the fuzzy set is assigned a membership grade. A higher grade represents a higher degree of set membership. Such a function is called the membership function and is denoted as \( \mu_A(x) \).

For a discrete set, a special notation is often used in the literature to represent fuzzy sets. Assume that \( x_1 \) to \( x_n \) are elements of a fuzzy set \( A \), and \( \mu_1 \) to \( \mu_n \) are their grades of membership in \( A \). The fuzzy set \( A \) is usually represented as:

\[
A = \frac{\mu_1}{x_1} + \frac{\mu_2}{x_2} + \cdots + \frac{\mu_n}{x_n}
\]  

(1)

For a continuous set, the fuzzy set \( A \) is represented as:

\[
A = \int_x \frac{\mu(y)}{y} dy
\]  

(2)

The basic operations on fuzzy sets are complementation, union, and intersection. They are defined as follows:

(1) The complementation of a fuzzy set \( A \) is denoted as \( \neg A \), and its membership function is defined as:

\[
\mu_{\neg A}(x) = 1 - \mu_A(x), \quad \forall x \in X
\]  

(3)

(2) The intersection of two fuzzy sets \( A \) and \( B \) is denoted as \( A \cap B \) and its membership function is defined as:

\[
\mu_{A \cap B}(x) = \min \{ \mu_A(x), \mu_B(x) \}, \quad \forall x \in X
\]  

(4)

(3) The union of two fuzzy sets \( A \) and \( B \) is denoted as \( A \cup B \) and its membership function is defined as:

\[
\mu_{A \cup B}(x) = \max \{ \mu_A(x), \mu_B(x) \}, \quad \forall x \in X
\]  

(5)

2.2. The original rough set approach

The original rough set theory proposed by Pawlak (1982, 1997) is based on the assumption that data and information are associated with every object of the universe of discourse. Objects characterized by the same properly selected information (referred to as attributes or features) are indiscernible in view of the available information. Data of the objects, i.e., attribute values, are often presented in an information table or decision table (Polkowski and Skowron, 1998). The columns are the attributes (features), and the rows are the objects.

It is possible that some attributes in an information table are irrelevant to discern dependency on the decision attributes. When all redundant attributes are removed without losing any essential information, the remaining subset that contains only the essential attributes is called a reduct. There could be multiple of reducts in an information table.