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IETM centered intelligent maintenance system integrating fuzzy semantic inference and data fusion

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ABSTRACT

This paper presents a novel interactive electronic technical manual (IETM) centered intelligent maintenance system, which integrates diagnosis strategies of *experience*-based manual interpretation, *rule*-based fuzzy semantic inference and *condition*-based data fusion. Firstly, initial judgment is tried by onsite maintainer; otherwise rule-based fuzzy semantic inference is proposed on the designed IETM platform for rapid diagnosis using portable maintenance aid (PMA). For condition monitoring subsystems, signals can be collected and download to ground station via PMA for enhanced diagnosis using advanced classifiers and data fusion techniques. The combined diagnostic strategies are employed to trigger maintenance guidance and relevant works such as spare parts management etc. The proposed scheme was evaluated by two experiments of fault diagnosis for electric multiple units (EMU) trains. Experiment results show that *intelligent*, *convenient*, *accurate* and *flexible* diagnosis advantages can be obtained, which are benefit to maintenance reality.

1. Introduction

For many systems, like manufacturing and transportation systems, maintenance activities have a major influence on the availability, safety, and operational costs of the system [1]. Since the development of the concept of preventive maintenance, maintenance practices have evolved from being *manual*-centric inspection to *information*-centric analysis. The rapid advancement of information and communication technologies and the integration of advanced analytics into manufacturing, products and services, many industries are facing new opportunities. This integration is called Cyber-physical Systems (CPS) [2]. A typical application of CPS on maintenance is the IETM-based interactive system.

The IETM [3] is defined as a data integration information packet used for engineering system diagnosis, service and maintenance process. To compare with drawbacks of the paper technology material such as big volume, inconveniently use, difficultly update, data redundancy, IETM can provide technical instructing and information support to user timely, usefully and necessarily with good interactivity [4]. It can show formatted electronic data on the electron screen for the requirements of users. Embedded into a PMA, the IETM can adopt mode combination of B/S and C/S to establish the united equipment management and maintenance information system [5].

In past two decades, most work about IETM were focused on the technical document digitization and interactive query, which only reached functions of level 2 according to S1000D Issue 2.0 [6]. Slow progresses were obtained to integrate IETM with expert system for intelligent maintenance until recent years. The current issues are mainly concentrated in:

1) How to utilize massive semantic records and monitoring data for *intelligent* reasoning?
2) How to construct a *convenient* diagnosis infrastructure for IETM centered intelligent maintenance system?
3) How to improve *accuracy* of fault diagnosis?

To cope with these challenges, this paper develops a hybrid diagnosis scheme for a designed IETM centered intelligent maintenance system as shown in Fig. 1, which combines strategies of *experience*-based manual interpretation, *rule*-based fuzzy semantic inference and *condition*-based fusion diagnosis. First of all, initial inspection activity is carried according to personal observation and experiences; then a rapid diagnosis, using PMA, can be run on IETM software platform by ticking out anomaly symptoms and assign criticality for fuzzy semantic inference. For monitoring subsystems or line replaceable units (LRUs), operating data are collected and download to ground station for enhanced diagnosis using multi-classifier and data fusion algorithms. Final diagnosis decisions via PMA can active technical guidance for troubleshoot and maintenance. The relevant information of BOM (Bill of Material) and spare can be updated synchronously with maintenance. The

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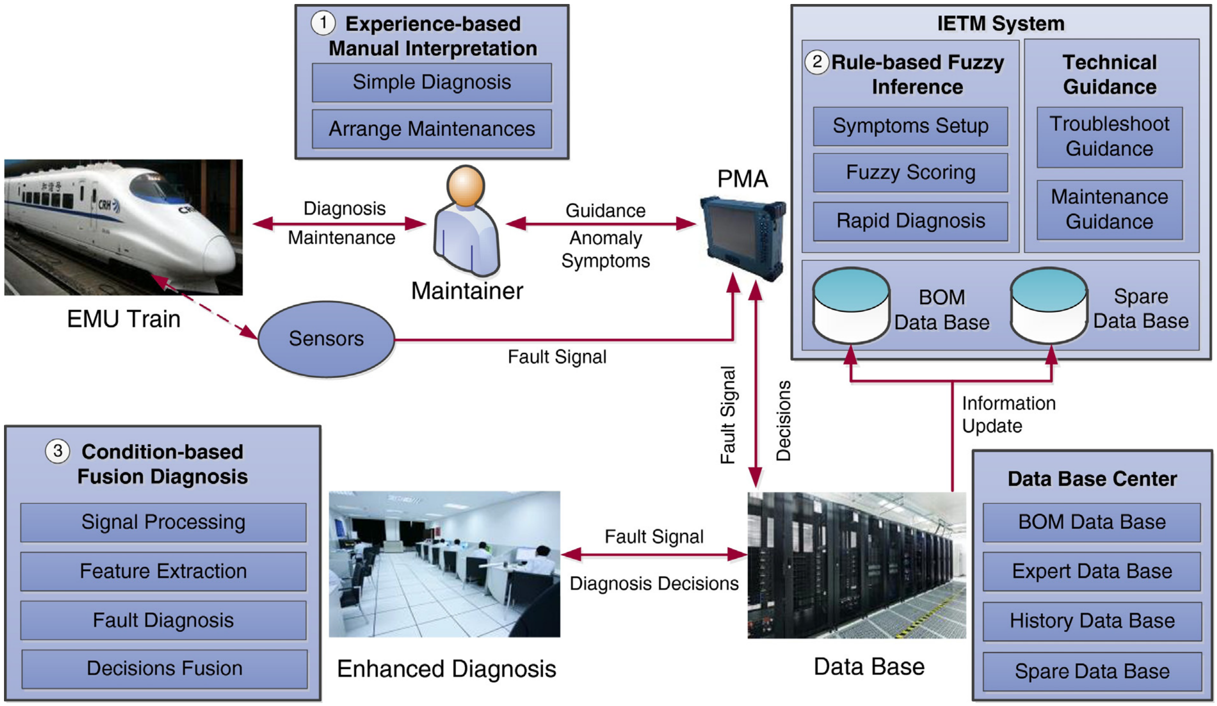

Fig. 1. Schematic of designed IETM centered intelligent maintenance system.

proposed scheme can provide *intelligent*, *convenient*, *accurate* and *flexible* diagnosis advantages, which are benefit to actual maintenance.

The remaining parts of this paper are organized as follows. Section 2 introduces the relevant knowledge of cosine similarity, fuzzy semantic inference and data fusion. In Section 3, the proposed hybrid diagnosis scheme and designed IETM centered intelligent maintenance system are developed in detail. Section 4 describes two experiments of fault diagnosis for EMU train to evaluate performance of the proposed strategy. Finally, the conclusions are given in Section 5.

2. Description of background knowledge

The traditional diagnosis function of IETM mainly depends on rule-based approach [7]. Its typical implementation is case-based reasoning (CBR) that uses expert-defined rules in the form of decision trees, as well as automatically generated rules from the samples stored in the case base [8]. These rules reflect essential relationships within the domain. When specific information about the domain becomes available, the rules are used to draw conclusions and to point out appropriate actions. It takes place as a kind of chain reaction. However, this kind of inference cannot change flexibly according to different scenes. Lots of useless rules often have to be checked step by step before actual fault is troubleshooted, which leads to low efficiency. This section introduces relevant background knowledge used in the developed scheme, including cosine similarity for records standardlization, fuzzy semantic inference for rapid diagnosis and data fusion for enhanced diagnosis.

2.1. Cosine similarity

Cosine similarity is a metric that is commonly used, particularly in high-dimensional positive spaces, to perform tasks such as information retrieval [9] and data mining [10]. Unlike the Euclidean distance, which suffers from a high sensitivity to even a small deformation, cosine similarity pays more attention to directions than absolute values. This significant advantage makes it especially suitable for similarity calculation between standard semantic symptom vectors and fault record vectors.

In mathematics, it measures similarity as the cosine of the angle between the two vectors. Two similar vectors are expected to have a small angle between them. The cosine similarity of two patterns **s** and **s**´ is defined by

$$\cos(\theta) = \frac{\sum_{i=1}^{d}(\mathbf{s}_i \times \mathbf{s}'_i)}{\sqrt{\sum_{i=1}^{d}\mathbf{s}_i^2} \times \sqrt{\sum_{i=1}^{d}\mathbf{s}_i'^2}} \quad (1)$$

where θ is the angle between **s** and **s**′. The basic principle of this algorithm is that the smaller the cosine angle is, the greater the similarity of two samples owns. If the two spectra are entirely identical, the $\cos(\theta) = 1$, the two samples in the pattern space get close to one point, and vice versa.

In terms of semantic symptom, it can be mainly divided into three content words: subject (S), predicate (P) and object (O). We use $\mathbf{s}_{\mathbf{word}}$ represents a set of standard semantic symptoms, which consists of all similar semantic in original symptoms for all faulty records. A unit vector $\mathbf{s}_{\mathbf{num}}$ is appointed to represent $\mathbf{s}_{\mathbf{word}}$ numerically. Then search $\mathbf{s}_{\mathbf{word}}$ in original symptoms of each faulty record. If some element of $\mathbf{s}_{\mathbf{word}}$ is found, then the corresponding element of $\mathbf{s}_{\mathbf{num}}$ is kept as 1, otherwise is set as 0. As a result, a new numerical vector $\mathbf{s}_{\mathbf{num}}'$ is constructed. Next, cosine similarity between $\mathbf{s}_{\mathbf{num}}$ and $\mathbf{s}_{\mathbf{num}}'$ can be calculated, and the result is compared with a predetermined metric. If the calculated similarity is large than the metric, it is believed that this record includes the standard semantic symptom $\mathbf{s}_{\mathbf{word}}$, and use it replace the original symptom. Finally, original symptoms for all faulty records are normalized and the like.

2.2. Fuzzy logic algorithm

The term fuzzy logic was introduced with the 1965 proposal of fuzzy set theory by Lotfi Zadeh [11,12,13]. Fuzzy set theory and fuzzy logic have proved to be suitable formalisms to handle imprecise semantics knowledge [14]. It has been applied to solve diagnosis problems of non-deterministic semantics and fuzzy concepts.

Assume that D is a set of fault symptoms, $D = \{D_1, D_2 \ldots, D_n\}$, d_i represents the state variable of D_i. The fuzzy fault symptom vector **f** can be