A Survey of Fault Diagnosis Methods for Micro Embedded Systems: Postprint

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Abstract

With the rapid development of the Internet of Things and big data, micro-embedded systems have been widely applied in industries such as food delivery, bike-sharing, transportation, courier services, and smart homes. Existing fault diagnosis research primarily focuses on traditional embedded systems, resulting in relatively scarce literature on fault diagnosis for micro-embedded systems. To address this issue and considering the characteristics of these systems (limited computational capacity and storage space), a classification method for fault diagnosis approaches suitable for micro-embedded systems is proposed, dividing them into two major categories: local fault diagnosis methods and remote fault diagnosis methods. The core ideas of fault diagnosis methods for micro-embedded systems are then described, the advantages and disadvantages of each method when applied to micro-embedded systems and critical considerations are summarized, and finally, the urgent problems to be solved in fault diagnosis for micro-embedded systems are discussed.

Full Text

Preamble

Title: Review of Fault Diagnosis Methods for Micro-Embedded Systems

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Abstract: With the rapid development of the Internet of Things and big data, micro-embedded systems have been widely deployed in industries such as food delivery, bike-sharing, transportation, logistics, and smart home automation. However, existing fault diagnosis research primarily focuses on traditional embedded systems, resulting in relatively scarce literature specifically addressing micro-embedded system fault diagnosis. To address this gap and account for the inherent characteristics of these systems—namely limited computing capacity and storage space—this paper proposes a classification framework for fault diagnosis methods suitable for micro-embedded systems. The framework organizes methods into two major categories: local fault diagnosis methods and remote fault diagnosis methods. We elaborate on the core principles of each approach, summarize their respective advantages and disadvantages when applied to micro-embedded systems, identify key implementation considerations, and finally discuss critical unresolved challenges in this domain.

Keywords: micro-embedded system; fault diagnosis; qualitative diagnosis; quantitative diagnosis

Introduction

Micro-embedded systems represent a smaller-scale subset of traditional embedded systems, typically featuring operating systems ranging from a few kilobytes to several hundred kilobytes in size. Consequently, these systems exhibit higher integration, more specialized functionality, and more severe resource constraints compared to conventional embedded systems. Their limited computational power and restricted storage capacity also make secondary development particularly challenging. Representative applications include POS terminals and receipt printers in the printing industry, smart locks for bike-sharing systems and fingerprint locks for security doors in the security sector, heart rate and pulse monitors and rehabilitation training equipment in healthcare, and smart music players, smart headphones, and smart furniture in everyday consumer electronics.

While these micro-embedded systems provide users with enhanced security and convenience, their increasing daily usage frequency has led to a proliferation of fault types and higher failure rates. Examples include smart lock malfunctions in popular bike-sharing and car-sharing services, and subsystem failures in smart home systems. Traditional fault diagnosis methods, developed under the assumption of abundant resources, struggle to address these challenges effectively. Although fault diagnosis techniques have been studied since the 1970s and numerous methods exist, research specifically targeting micro-embedded systems remains limited. By analyzing traditional fault diagnosis approaches and existing classification frameworks in conjunction with the unique characteristics of micro-embedded systems, this paper proposes a novel classification framework tailored to this domain, as illustrated in [Figure 1: see original paper]. We provide detailed explanations and comparisons of each method, and identify pressing issues that require resolution.

Micro-embedded systems generally implement fault diagnosis in two stages: preliminary diagnosis and detailed diagnosis. Preliminary diagnosis employs simple models with low computational requirements to identify basic system faults effectively. Due to the inherent constraints of micro-embedded systems, these preliminary models must provide comprehensive system coverage and supply valid data support for detailed diagnosis. However, preliminary diagnosis alone cannot achieve high precision for complex faults, necessitating server-based analysis of preliminary diagnostic data combined with advanced artificial intelligence methods for more accurate fault identification.

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1 Local Fault Diagnosis Methods

Local fault diagnosis methods refer to approaches where micro-embedded systems perform preliminary diagnosis and analysis using locally collected data. Given the resource limitations, high integration, and difficult secondary development characteristics of micro-embedded systems, local diagnosis methods primarily address fundamental fault detection and provide diagnostic data for remote analysis. These methods mainly include two qualitative graphical approaches: Signed Directed Graph (SDG) and Fault Tree Analysis (FTA).

1.1 Signed Directed Graph (SDG)

The SDG model is the most representative qualitative model for fault diagnosis. Its core principle involves identifying system nodes and branches in micro-embedded systems, then analyzing normal-state node data and branch relationships to establish causal relationships between nodes, which are graphically represented to locate fault sources. Iri et al. first proposed applying SDG models to fault diagnosis. The SDG model is fundamentally based on mathematical foundations and ultimately generates a Cause-Effect (CE) graph, with related concepts and definitions established in the literature. In 2005, Yang and Xiao provided a comprehensive summary of SDG models and definitions, presenting the mathematical formulation.

To apply SDG to micro-embedded systems, one only needs to determine node and branch relationships, enabling intuitive diagnostic models with clear logic. Moreover, node data can be transmitted to remote servers to assist with remote fault diagnosis. However, SDG algorithms are constrained by the number of nodes and branches; excessive branches and node information may cause redundancy, and node thresholds are difficult to determine precisely, potentially leading to erroneous fault cause information.

Researchers have proposed various enhancements to address these limitations. Liu et al. combined SDG models with rule-based systems to distinguish node states for fault diagnosis. Since node state values alone cannot reflect fault severity, Liu et al. later proposed a fuzzy five-range SDG model in 2015 that incorporates quantitative information to represent fault hazard levels, making it suitable for micro-embedded systems where node thresholds are difficult to establish. To handle cases where fault nodes may be influenced by multiple nodes, leading to misinterpretation, Peng et al. proposed a multi-logic probabilistic SDG model integrated with Bayesian inference. This approach uses logic gates to describe logical causal relationships among multiple nodes and employs backtracking to analyze the posterior probability of identified faults, thereby determining the true fault cause. For multiple fault scenarios in micro-embedded systems, Smaili et al. combined PCA (Principal Component Analysis) with SDG for fault detection and isolation. Liu et al. further proposed a fault diagnosis method based on probability-extended SDG and fault index reasoning, demonstrating through simulation that this approach achieves high fault resolution and is suitable for fault cause localization.

1.2 Fault Tree Analysis (FTA)

Fault Tree Analysis is a causal modeling approach that enables hierarchical decomposition of micro-embedded system failures from system-level to component-level. FTA categorizes faults into three event types: top events, intermediate events, and basic events. Top events represent system-level failures—the most undesirable outcomes that require state value determination. Intermediate events correspond to subsystem failures, while basic events represent component failures, though basic events may not necessarily trigger top events. For instance, a subsystem A failure might be caused by simultaneous failures of components 1 and 2.

FTA has been widely applied in fault diagnosis, particularly for micro-embedded systems with well-defined fault types and categories, such as receipt printer systems. However, the resource constraints of micro-embedded systems can complicate multiple fault identification. To address this, Shakeri et al. proposed several sorting algorithms for multiple fault isolation problems, establishing relationships between suboptimal performance and computational complexity that significantly reduce the storage complexity of overall diagnostic strategies. Ge et al. proposed an online analysis method for unexpected faults in real-time embedded systems using Hidden Markov Models (HMM), combining probability theory from fault trees and Bayesian networks to identify complex faults through extensive case studies. Yuan and Chu demonstrated the effectiveness of combining SVM (Support Vector Machine) with FTA for fault classification and priority assessment, validated through turbo-pump rotor fault diagnosis.

To enhance reasoning capabilities, Yang proposed integrating FTA and FMEA (Failure Mode and Effects Analysis) to create a Bayesian network-based fault diagnosis model. Chen et al. developed a System-Phenomenon-Fault tree approach based on FTA that effectively narrows fault search scope and reduces computational difficulty. While FTA requires thorough understanding of system structure and function to summarize and quantitatively analyze top event probabilities, its strong logical foundation makes it valuable. However, different analysis perspectives may lead to variations in fault tree node construction, potentially affecting diagnostic accuracy.

2 Remote Fault Diagnosis Methods

Due to the limited storage and computational resources of micro-embedded systems, data analysis requiring substantial computation and complex fault diagnosis must be offloaded to remote servers. Combining advanced artificial intelligence diagnostic methods for remote fault diagnosis can significantly improve accuracy and even enable fault prediction.

2.1 Expert System (ES)

Given resource constraints, expert systems for micro-embedded systems are typically deployed on remote servers. These remote expert systems continuously collect data transmitted from micro-embedded systems, consult their knowledge bases when faults occur, and provide diagnostic feedback through inference engines, as illustrated in [Figure 4: see original paper].

Data transmission reliability and availability are critical considerations for remote expert system implementation. Ding designed a database update model for remote expert systems to address these concerns. Zhang et al. proposed a CLIPS expert system using DSP and CPLD data that features predefined processing, convenient knowledge base updates, and high diagnostic accuracy. After data processing, combining local fault diagnosis can generate relevant diagnostic knowledge. Li and Ji utilized fuzzy SDG technology to obtain system fault data and generate corresponding knowledge rules for online expert system diagnosis. Wang et al. demonstrated effective fault diagnosis for a digital control system control box using FTA data to build an expert system.

Expert system-based fault diagnosis offers intuitive and rapid fault localization without requiring precise mathematical models. However, it necessitates data preprocessing and extensive historical fault data support, which limited early applications in micro-embedded systems.

2.2 Empirical Mode Decomposition (EMD)

Empirical Mode Decomposition is widely applied in signal processing-based fault diagnosis. It decomposes signals transmitted from micro-embedded system local diagnosis into multiple Intrinsic Mode Functions (IMFs). EMD is an adaptive signal processing method suitable for nonlinear and non-stationary processes. The decomposition can be expressed as:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t)$$

where $x(t)$ is the original signal, $c_1(t)$ to $c_n(t)$ are the IMFs, and $r_n(t)$ is the residual. Each IMF represents a simple oscillation pattern. EMD is particularly effective for real-time diagnosis of non-stationary datasets in micro-embedded systems. However, decomposition into multiple IMFs may introduce noise issues that lead to inaccurate IMFs. To mitigate this, Meng et al. proposed a hybrid method combining wavelet transform with EMD for original signal preprocessing, reducing narrow-band pulses and random noise to improve fault detection accuracy. Gao et al. proposed fault identification through CMF (Combined Mode Function) recognition. Dybala and Zimroz further advanced this by aggregating IMFs into three patterns—noise, signal, and trend—which facilitates noise separation and improves early fault detection accuracy. Additionally, Zhang et al. optimized IMF extraction using SVM to classify IMFs and identify fault severity, demonstrating effective bearing fault recognition and improved system robustness. Amarnath and Krishna proposed optimizing IMF peaks to quantify various faults, proving beneficial for early equipment fault detection.

EMD is primarily applied to micro-embedded systems with non-stationary datasets, enabling rapid and accurate fault information extraction through signal data analysis. However, it cannot effectively identify stable or stationary signals.

2.3 Principal Component Analysis (PCA)

Principal Component Analysis collects normal historical data to study causal relationships among variables and identify low-dimensional components. The fault detection model is typically expressed as:

$$T^2 = SPE = \|(I - PP^T)z\|^2$$

where z is the standardized matrix, SPE is the fault statistic, and P is the eigenvector of Z. When collected data violates the condition $SPE > \partial^2$, a fault is indicated.

PCA is well-suited for micro-embedded systems with complex internal structures and numerous nodes. For systems with complex inter-node relationships that reduce diagnostic precision, Gharavian et al. proposed an FDA-based fault diagnosis method using PCA to reduce dimensionality of variables from variable-speed gearboxes, combined with other methods to improve accuracy. For data preprocessing, Ma et al. proposed a local neighborhood standardization (LNS) strategy, demonstrating through experiments that LNS-PCA outperforms traditional PCA in fault detection for multi-mode processes. While PCA synthesizes multi-variable data for fault detection, it cannot adequately explain fault causes. Lu et al. addressed this by combining PCA with SDG, using SDG to locate faults and analyze causes effectively. Wang et al. proposed a multi-level PCA approach to identify fault magnitude, proving capable of analyzing fault causes through simulation.

PCA requires operational data to follow normal distribution, making it less effective in multi-mode processes. However, it only needs key node historical data from micro-embedded systems, aligning well with remote fault diagnosis characteristics. The method demands strict data requirements and substantial historical data support, making it suitable for systems with extensive operational history.

2.4 Support Vector Machine (SVM)

Support Vector Machine is a crucial classification method in fault diagnosis. Its core principle in micro-embedded system applications involves comprehensive analysis of fault data and classification of fault features to achieve diagnosis. The basic mathematical model is:

$$f(x) = a\omega\phi(x) + b$$

where a and b are constants, and $\phi(x)$ is obtained through nonlinear transformation. The classification indicator is derived from this formulation.

SVM can effectively classify diagnostic data from local fault diagnosis, but classification rationality and effectiveness must be considered. Yang et al. proposed combining fractal dimension with SVM, evaluating each fractal dimension's classification performance to achieve fault diagnosis. To improve accuracy, Shen et al. developed a universal multi-category solver integrating wavelet packet transform (WPT), distance evaluation technique (DET), and support vector regression (SVR), effectively distinguishing bearing and gear faults while improving diagnostic accuracy. Shen et al. also proposed extracting non-stationary signal features through EMD combined with transformed SVM to enhance diagnostic precision.

SVM primarily classifies feature information from local fault diagnosis data in micro-embedded systems, enabling "soft fault" self-recovery through effective fault classification. However, relying solely on single-feature information may yield low accuracy for multiple faults, necessitating combination with other diagnostic methods.

2.5 Wavelet Transform

Wavelet Packet Transform (WPT) evolved from FFT (Fast Fourier Transform), which has been widely applied in traditional fault diagnosis but is limited to stationary signals. Wavelet transform' s ability to diagnose non-stationary signals has led to its extensive adoption. The most important and widely used form is Continuous Wavelet Transform (CWT), expressed as:

$$W(a,b) = \frac{1}{\sqrt{a}} \int x(t)\psi^* \left(\frac{t-b}{a}\right) dt$$

where a is the scale parameter, b is the time parameter, $\psi(t)$ is the wavelet basis function, and $\psi^*(t)$ is its complex conjugate.

Wavelet transform is suitable for micro-embedded systems with highly fluctuating datasets. Its core principle involves performing wavelet transform on local fault diagnosis data and extracting signal feature information to detect abrupt signal changes for fault diagnosis. While multiple fault identification is challenging, Seshadrinath et al. applied wavelet transform combined with SVM to embedded variable-frequency motor systems, using SVM for fault classification and complex wavelets for multiple fault identification and separation. Bennouna and Roux developed a wavelet transform-based reliability diagnosis program for embedded systems, demonstrating robust performance across different fault scenarios.

Wavelet transform can effectively and rapidly identify signal mutations for real-time fault diagnosis. However, its strong constraints mean results are affected by wavelet basis selection, decomposition levels, and wavelet function parameters, resulting in limited adaptability.

2.6 Artificial Neural Network (ANN)

Artificial Neural Network applications in fault diagnosis primarily utilize the BP neural network model, which consists of three layers as shown in [Figure 5: see original paper]: input layer, hidden layer, and output layer. With freely configurable hidden nodes, this three-layer structure can approximate any continuous function.

ANN typically serves as an auxiliary tool for remote fault diagnosis in micro-embedded systems. For example, Ali et al. extracted nonlinear bearing features using EMD and trained an ANN for defect classification, successfully enabling online defect severity detection. Zhou et al. combined PCA-extracted principal features with neural networks for effective fault detection and identification across multiple processes. Zhang et al. preprocessed vibration signals from sensors using wavelet decomposition and Fourier transform, then trained an ANN to predict remaining useful life and identify component faults. Wang et al. overcame traditional expert system limitations by integrating ANN with fault tree-based expert systems, demonstrating an efficient and reliable novel approach.

ANN addresses knowledge acquisition, unknown knowledge representation, and parallel reasoning issues in diagnostic systems through continuous learning and training from remote diagnostic fault data. However, it requires substantial sample support during initial stages, resulting in lower early-stage diagnostic accuracy.

2.7 Comparative Analysis of Methods

Micro-embedded system diagnostic methods can be categorized into remote and local approaches. Local diagnosis methods employ qualitative techniques suited to the resource constraints, high integration, and difficult secondary development characteristics of micro-embedded systems. These methods are intuitive, easy to understand, and enable rapid fault detection and source analysis. Remote diagnosis methods perform more precise analysis on local diagnostic data, effectively improving diagnostic accuracy, enhancing local methods, and enabling fault prediction. Based on literature review, we present a comparative analysis of fault diagnosis methods in .

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3 Conclusion

With the rapid development of micro-embedded systems in the IoT domain, fault diagnosis research holds significant application value across industries such as transportation (“warehouse printer cluster systems”), bike-sharing (“smart lock systems”), and smart home (“control systems”). Effectively utilizing local fault diagnosis data to rapidly build diagnostic models and perform remote fault diagnosis represents a critical advancement. This paper has reviewed recent domestic and international trends, summarized advantages and disadvantages of existing technologies, and identified several pressing challenges:

a) **Multiple fault detection and isolation**: Single diagnostic methods often cannot effectively detect and isolate faults in complex systems. Since multiple faults frequently occur in complex systems, accurately and rapidly detecting and isolating them through hybrid diagnostic approaches remains an urgent problem.

b) **Novel fault identification**: While methods such as SDG, PCA, fault tree analysis, and artificial neural networks can identify faults, they all rely on extensive historical fault data. Early identification of novel faults with limited historical data has been a persistent challenge.

c) **Fault prediction and self-repair**: Current micro-embedded system fault diagnosis methods primarily address post-failure scenarios, enabling only passive diagnosis. Proactively predicting when and why faults will occur through data monitoring and diagnostic techniques before failure happens, thereby enabling fault prediction and self-repair, represents a challenging yet promising research direction.

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