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Zero-shot Diagnosis of Compound Faults Based on Circuit Operational Mechanism

Zhongyu Gao[1], Aibin Yan[2], Hanxiang Li[2], Gaoyang Shan[3], Jehad Ali[3], Xiaoqing Wen[4], Patrick Girard[5]

[1]*School of Computer Science and Technology, Anhui University, China*
[2]*School of Microelectronics, Hefei University of Technology, China*
[3]*Department of AI Convergence Network, Ajou University, Seoul, South Korea*
[4]*Department of Computer Science and Networks, Kyushu Institute of Technology, Japan*
[5]*LIRMM, University of Montpellier/CNRS, France*

***Abstract*—Existing fault diagnosis schemes for analog circuits rely on comprehensive fault data, posing significant limitations in industrial applications. On the one hand, compound faults in circuits arise from the coupling of multiple single faults (SFs), leading to a scarcity of fault samples compared to SFs. On the other hand, the number of compound fault categories grows exponentially compared to SFs, making it impossible to collect sufficient and comprehensive data. This study focuses on the zero-shot diagnosis task under real-world conditions, aiming to achieve accurate diagnosis of compound faults by solely utilizing SF data. To this end, based on the circuit operation mechanism, we extract fault patterns from SF data. Subsequently, we utilize both the SF data and the extracted fault patterns to generate high-quality pseudo-compound fault data. Finally, the final diagnostic decision is derived through dynamic fusion of classification results based on similarity assessment. Multiple analog circuits-based experiments with varying complexity validate the universality and effectiveness of the proposed scheme, achieving accuracies of 68.43%, 74.70%, and 73.27%, respectively, without using any composite fault data.**

***Keywords*—Compound fault diagnosis, Generative zero-shot learning, Similarity-based decision classifier**

I. Introduction

Analog circuits (ACs), enabling signal generation, arithmetic operations, amplification, and filtering, are extensively utilized in industrial equipment with their stability vital for safe operation as basic electronic device supports [1]. Accurately assessing their operational status in electrical instruments under harsh conditions is crucial [2]. In recent years, machine learning's industry success has spurred more data-driven solutions for AC fault diagnosis [3-8]. While existing research has yielded abundant results on single faults (SFs), it rarely tackles compound faults in ACs [2]. Compound faults, with complex causes and exponentially growing types due to coupling, make comprehensive data collection nearly impossible, undermining existing data-driven approaches.

Zero-shot learning (ZSL) has garnered significant attention for its capacity to recognize unseen class objects using knowledge from seen classes [9], mitigating the challenge of difficult fault data acquisition in fault diagnosis as it doesn't require target task data. In this field, Fault Description-based Attribute Transfer (FDAT) [10] enables multi-attribute data annotation via training multiple attribute classifiers, directly learning data-attribute correlations. Hu et al. [11] enhanced FDAT with Semantic Consistent Embedding (SCE), embedding fault samples and attribute labels into a semantically consistent space for consistent cross-modal embeddings and direct attribute prediction, improving accuracy. Xu et al. [12] introduced a zero-shot fault semantics learning model for unknown compound fault diagnosis, constructing semantic information unsupervised, learning feature-semantics mapping, generating composite fault features for judgment, and determining fault categories by distance comparison. Xian et al. [13] proposed a GAN synthesizing features from class-level semantics to train classifiers, while Schonfeld et al. [14] used aligned Variational Autoencoders (VAE) to learn a shared space for image features and class embeddings, constructing multimodal latent features for unseen category classification.

ACs have numerous fault categories and high data confusion, leading to poor zero-shot diagnostic performance. Expert-dependent prior information construction also raises training costs. Analog circuits' rich electrical traits, especially continuity from Kirchhoff's and Ohm's Laws, prompt us to exploit these features. We propose a novel Zero-Shot Learning (ZSL) data generation model that generates pseudo-compound fault data by integrating existing SF data. The main contributions are as follows:

1. A novel zero-shot scheme is proposed for compound fault diagnosis in ACs. It can effectively accomplish the task of compound fault diagnosis using only SF data without requiring additional information annotation.
2. A novel similarity-based decision classifier (SDC) is introduced. It makes dynamic decisions by estimating the distribution similarity between real data and pseudo-data to generate more accurate diagnostic results.
3. Comprehensive experiments have been conducted on multiple circuit diagnostic tasks with varying levels of complexity to verify the universality and effectiveness of the proposed scheme.

II. Proposed Methodology

A. Problem Definition

We transform the compound fault diagnosis problem into a ZSL problem. The training set x_s solely comprises SF and NF samples, while the test set x_u contains compound fault samples from M categories. x_s and x_u have different data distributions and disjoint classes. We focus on the double coupled compound faults (DFs) as they are the most common and high-probability type of compound faults [2].

B. Model Structure

The overall architecture of the proposed scheme is shown in Fig. 1, which includes a data collection module, a pattern extraction and pseudo-compound fault generation module, and a similarity-based decision classifier.

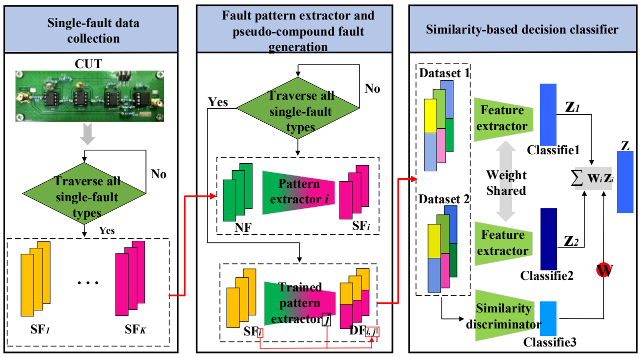


Fig. 1. The proposed zero-shot fault diagnosis scheme for compound faults in ACs.

Data Collection: For the test circuit, we respectively collect a NF dataset NF and a SF dataset SF_k. Among them, the SF dataset SF_k contains data from K single-fault categories.

Pattern Extractor Network (PEN): Faults in ACs exhibit physical traceability. Based on this characteristic, by performing specific feature transformation operations on normal-state data, the data distribution characteristics corresponding to fault states can be reconstructed.

We construct the PEN by traversing various types of fault data and conducting supervised training separately to capture the pattern transformation process between NF data and SF data, which can be represented as follows:

$$PEN_k(x_{NF}) \rightarrow x_{SF} \tag{1}$$

The pattern extraction models for all SF categories constitute a set named $SET_{PEN} = \{PEN_k \mid k = 1,2...,K\}$ for all seen classes. The proposed PEN architecture is illustrated in Fig. 2.

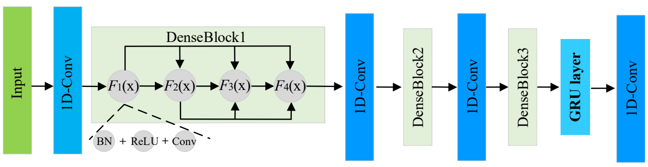


Fig. 2. The structure of pattern extractor network.

Pseudo-Fault Data Generation: We conduct a causal analysis of DFs to identify the SF categories, i and j, that lead to their occurrence. Subsequently, employing a traversal approach, we filter out category-i fault data from the single-fault dataset SF_k, denoted as SF_i. Simultaneously, we select a category-j PEN_j from the network set SET_{PEN}. Finally, we apply the chosen PEN_j to perform pattern transformation operations on the sample set SF_i, thereby generating a pseudo-compound fault sample set.

$$PEN_i(SF_j) \rightarrow DF_{i,j} \tag{2}$$

Similarity-based Decision Classifier (SDC): The framework proposed in the pseudo-data generation module can generate differentiated data of the same category by swapping the order of indices as below.

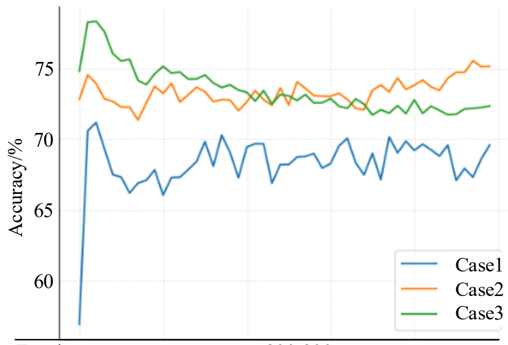
$$PEN_i(SF_j) \rightarrow DF_{i,j} = PEN_j(SF_i) \rightarrow DF_{j,i} \tag{3}$$

For this purpose, we propose a classifier that integrates distribution similarity decision to better handle multi-source datasets. As depicted on the right of Fig.1, the architecture comprises a feature extractor (Fea), a similarity discriminator, and three task classifiers (Classifier1, Classifier2, Classifier3). The feature extractor extracts discriminative features, especially those linked to fault patterns, while the similarity discriminator focuses on data source-related features. Notably, the feature extractor and similarity discriminator share the same network structure. Classifier1 and Classifier2 predict fault patterns, whereas Classifier3 predicts feature sources.

III. Experimental Results

To assess our zero-shot diagnostic method's universality and effectiveness, three analog circuits (ACs) of differing complexity—Sallen-Key bandpass, four-op-amp biquad high-pass, and leapfrog filters—were tested [2]. Resistor and capacitor tolerances were 5% and 10%, with component fault severity deviating by 40%-50%. The circuits had 8/24, 10/40, and 12/60 single-fault (SF)/double-fault (DF) types, respectively. A 5V, 10-microsecond pulse signal served as the test excitation. Output signals for each SF type occurring 1000 times were collected as the training set, while those for each DF type occurring 1000 times formed the test set.

As shown in Fig. 3, model performance stabilized with more training epochs. Using average accuracy from epochs 300-400 as the metric, the compound fault diagnosis accuracies for the three circuits were approximately 68.43%, 74.70%, and 73.27%, respectively.



Epochs	0-100	100-200	200-300	300-400	400-500
Circuit1	67.10%	64.16%	66.67%	68.43%	67.91%
Circuit2	73.92%	74.04%	74.52%	74.70%	75.19%
Circuit3	77.90%	74.27%	73.93%	73.27%	73.25%

Fig. 3. Classification accuracy for different cases as the number of training epochs increases.

We compared our proposed approach with the state-of-the-art ZSL models in the diagnostic field, including FDAT [10], SCE [11], ZFSL [12], CADA_VAE [14], LIV-ZSL [15], ACGAN-FG [16], and CycleGAN-SD [17].

Table I
Comparison of Accuracy of our Model with the State-of-the-art ZSL Models in Different Tasks.

Accuracy	Circuit1	Circuit2	Circuit3
FDAT [10]	14.16%	13.21%	18.34%
SCE [11]	16.12%	15.63%	18.69%
ZFSL [12]	31.83%	27.18%	19.27%
CADA_VAE [14]	37.84%	30.54%	16.76%
LIV-ZSL [15]	41.56%	37.19%	25.18%
ACGAN-FG [16]	37.66%	31.52%	22.21%
CycleGAN-SD [17]	28.62%	26.35%	19.73%
Ours	68.43%	74.70%	73.27%

As shown in Table I, the proposed scheme achieves the best classification performance in all three circuits, with an average accuracy rate as high as 72.13%.

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