A Fault Detection and Diagnosis Method for Analog Circuits Based on Task Transfer Learning

Zhongyu Gao[††], Xiaoqing Wen[†††] and Aibin Yan[†, ††]
[†]School of Microelectronics, Hefei University of Technology, Hefei 230601, China
[††]School of Computer Science and Technology, Anhui University, Hefei 230601, China
[†††]Department of Computer Science and Networks, Kyushu Institute of Technology, Fukuoka 8208502, Japan
(Contact Author: abyan@mail.ustc.edu.cn)

***Abstract*—This talk presents a fault detection and diagnosis method for analog circuits based on task transfer learning. To model the interconnections of circuit nodes, the sample data is organized into a graph-structure, and an unsupervised graph-based structural feature fusion method is proposed. To improve the model performance under few-shot conditions, transfer learning mechanisms are proposed for the topological structure features of analog circuits. Through parameter-shared strategy, a task transfer-based fault diagnosis approach is presented.**

I. Introduction

FAULT diagnosis is crucial for determining a system's conditions and then carrying out root-cause analysis [1]. Accurate diagnostic results are crucial for the safety and reliability of systems [2-3]. Surveys have revealed that 80% of industrial faults originate from analog circuits [4]. Therefore, developing methods for diagnosing faults in analog circuits is a key focus on addressing malfunctions of circuits. In electronic systems, data-driven based methods are widely employed due to their independence from empirical knowledge and the ease of generating diagnostic models [5-10], and they typically require enough labeled data for model training. In industrial fault diagnosis, it is challenging to collect fault data effectively [11]. Data-driven based methods have been widely applied, such as deep learning [12] and reinforcement learning [13]. Auto-encoder (AE) and transfer learning (TL) are important branches for representation learning. AE, consisting of an encoder, a bottleneck layer, and a decoder [14], is an unsupervised learning method primarily used for dimensionality reduction and feature extraction. Due to the unsupervised attribute, it is also frequently utilized in the field of anomaly detection [15]. The core of TL is to transfer knowledge learned from a source task to another different-yet-related target task to enhance the performance of the target task [16]. Common TL methods include feature-based, sample-based, relationship-based, and model-based ones [17]. By using the model and knowledge from the source task, TL can achieve better performance on the target task with less data and computational resources [18]. Moreover, to enhance the accuracy of circuit fault identification, it is particularly important to explore the correlations among node signals [19] and fault diagnosis aims to further analyze and determine the type of faults after detection [20].

II. Proposed Fault Detection and Diagnosis Method

We first design a relationship transfer mechanism utilizing GA^2E to extract potential topological relationships in circuits. As shown in Fig. 1(a), we obtain two circuits, i.e., C1 and C2, which exhibit topological structural similarities under assuming that it is challenging to obtain data from C2, and both datasets are limited to fault-free samples. We refer to G1 as the source domain and G2 as the target domain. G1 has abundant samples, while G2 has few-shot samples. Subsequently, GA^2E is employed to train on G1 to extract the relationship coefficient matrix among nodes. The specific process of circuit relationship extraction and relationship transfer include relationship extraction and circuit node relation transfer. Finally, we use GA^2E to train on G2.

Note that the data from different circuit nodes may have identical data features and thus we design a data transfer mechanism. As shown in Fig. 1(b), we acquire the source domain and target domain data, and then perform regularization on the source domain data G1. Regularization aims to match the value distribution of the data in G1 with that of G2, thereby eliminating data distribution differences. This process is implemented using Alg. 1. Next, to select suitable samples from the regularized G1, we use a weight list W to represent the probability of each sample being chosen from the regularized G1. Combining W, we extract a portion of the sample data from the regularized G1 and merge it with G2 to form a mixed dataset G3. Then, we use GA^2E to train G3. Finally, we can obtain the source domain data that is most relevant to the target task based on W, which is achieved using Alg. 2. Transferring these data can effectively address the issues associated with training on few-shot samples, providing an accurate fault detection model for data-scarce circuits.

Due to the similarity in feature representation between the source task and the target task, TL can be applied. We consider the fault detection task model as the source and the fault diagnosis task model as the target. We propose the GA^2E_Class network based on graph convolution for fault diagnosis. The transferred model includes the GATConv layer and Encoder layer trained in the detection task, which are used as pre-trained models in the fault diagnosis task, as shown in Fig. 1(c). Assuming an input feature matrix, after passing through the GATConv layer, Encoder layer, and Conv1D encoding, the output is *Y*. Due to the presence of multiple faults in circuit data, the fault types are encoded using the one-hot encoding. Based on this, a mapping relationship between the encoded feature and the diagnosis result *Z* is constructed. To minimize the difference between the label *L* and the predicted result *Z*, we update the network weight parameters using the cross-entropy loss function. The model transfer-based approach allows for parameter sharing to improve training efficiency. Considering that it is difficult to obtain faulty samples in practical applications, only few-shot fault samples are used for training. We selected three commonly used circuits from existing works [21-22] as shown in Fig. 2 and experimental results demonstrate the efficiency of the proposed method.

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References

[1] Z. Du, X. Chen, H. Zhang, H. Miao, Y. Guo, and B. Yang, "Feature identification with compressive measurements for machine fault diagnosis," *IEEE Transactions on Instrumentation and Measurement*, vol. 65, no. 5, pp. 977-987, May. 2016.

[2] H. Chen, B. Jiang, SX. Ding, and B. Huang, "Data-driven fault diagnosis for traction systems in high-speed trains: a survey, challenges and perspectives," *IEEE Transactions on Intelligent Transportation Systems*, vol. 23, no. 3, pp. 1700–1716, Mar. 2022.

[3] D. Stucchi, L. Magri, D. Carrera, and G. Boracchi, "Multimodal batch-wise change detection," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 34, no. 10, pp. 6783-6797, Oct. 2023.

[4] F. Li, and PY. Woo, "Fault detection for linear analog IC--the method of short-circuit admittance parameters," *IEEE Transactions on Circuits & Systems Part I Fundamental Theory & Applications*, vol.49, pp.105-108, Jan. 2002.

[5] G. Xu, G. Wen, D. Zhe, and L, Wei-dong, "Research on WNN soft fault diagnosis for analog circuit based on adaptive UKF algorithm," *Applied Soft Computing,* vol. 50, pp. 252-259, Jan. 2017.

[6] G. Zhao, X. Liu, B. Zhang, Y. Liu, G. Niu, and C. Hu, "A novel approach for analog circuit fault diagnosis based on deep belief network," *Measurement,* vol. 121, pp. 170-178, Jun. 2018.

[7] C. Zhang, Y. He, L. Zuo, J. Wang, and W. He, "A novel approach to diagnosis of analog circuit incipient faults based on KECA and OAO LSSVM," *Metrology and Measurement Systems,* vol. 221, pp. 108297, May. 2022.

[8] T. Gao, J. Yang, S. Jiang, and C. Yang, "A novel fault diagnostic method for analog circuits using frequency response features," *Review of Scientific Instruments,* vol. 90, pp. 104708, Oct. 2019.

[9] H. Yang, C. Meng, and C. Wang, "Data-driven feature extraction for analog circuit fault diagnosis using 1-D convolutional neural network," *IEEE Access*, vol. 8, pp. 18305-18315, Jan. 2020.

[10] M. Gebregiorgis, Y. He, S. Ning, and S. Wang, "Fault diagnosis method of analog circuit based on radial base function neural network," *Journal of Physics: Conference Series*, vol. 1575, no. 1, pp. 012148, May. 2020.

[11] J. Zhang, K. Zhang, Y. An, H. Luo, and S. Yin, "An integrated multitasking intelligent bearing fault diagnosis scheme based on representation learning under imbalanced sample condition," *IEEE Transactions on Neural Networks and Learning Systems*, early access, pp.1-12, Jan. 2023.

[12] S. Wang, S. Hu, B. Guo, and G. Wang, "Cross-region courier displacement for on-demand delivery with multi-agent reinforcement learning," *IEEE Transactions on Big Data*, vol. 9, no. 5, pp. 1321-1333, Oct. 2023.

[13] D. Li, and J. Dong, "Fuzzy control based on reinforcement learning and subsystem error derivatives for strict-feedback systems with an observer," *IEEE Transactions on Fuzzy Systems*, vol. 31, no. 8, pp. 2509-2521, Aug. 2023.

[14] H. Wen, W. Guo, and X. Li, "A novel deep clustering network using multi-representation autoencoder and adversarial learning for large cross-domain fault diagnosis of rolling bearings," *Expert Systems with Applications,* vol. 225, pp. 120066, Sep. 2023.

[15] X. Fang, J. Qu, Y. Chai, and B. Liu, "Adaptive multiscale and dual subnet convolutional auto-encoder for intermittent fault detection of analog circuits in noise environment," *ISA Transactions*, vol. 136, pp. 428-441, May. 2023.

[16] S. Ntalampiras, "One-shot learning for acoustic diagnosis of industrial machines," *Expert Systems with Applications,* vol. 178, pp. 114984, Sep. 2021.

[17] X. Chen, R. Yang, Y. Xue, M. Huang, R. Ferrero, and Z. Wang, "Deep transfer learning for bearing fault diagnosis: a systematic review since 2016," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1-21, Feb, 2023.

[18] X. Ni, D. Yang, H. Zhang, F. Qu, and J. Qin, "Time-series transfer learning: an early stage imbalance fault detection method based on feature enhancement and improved support vector data description," *IEEE Transactions on Industrial Electronics*, vol. 70, no. 8, pp. 8488-8498, Aug. 2023.

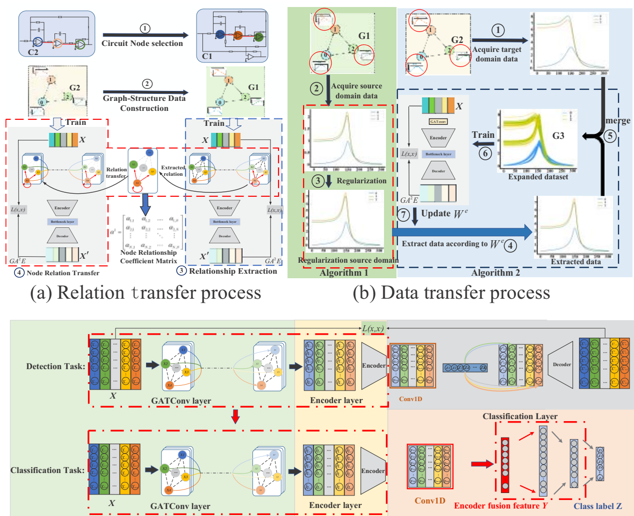
[19] J. Yang, Y. Li, and T. Gao, "An incipient fault diagnosis method based on Att-GCN for analogue circuits," *Measurement Science and Technology*, vol. 34, no. 4, pp.045002, Jan. 2023.

[20] R. Arunthavanathan, F. Khan, S. Ahmed, S. Imtiaz, and R. Risza, "Fault detection and diagnosis in process system using artificial intelligence-based cognitive technique," *Computers & Chemical Engineering*, vol.134, pp.106697, Mar. 2020.

[21] L. Ji, C. Fu, and W. Sun, "Soft fault diagnosis of analog circuits based on a ResNet with circuit spectrum map," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 68, no. 7, pp. 2841-2849, July 2021.

[22] T. Gao, J. Yang, and S. Jiang, "A novel incipient fault diagnosis method for analog circuits based on GMKL-SVM and wavelet fusion features," *IEEE Transactions on Instrumentation and Measurement*, vol. 70, pp. 1-15, Sep, 2021.

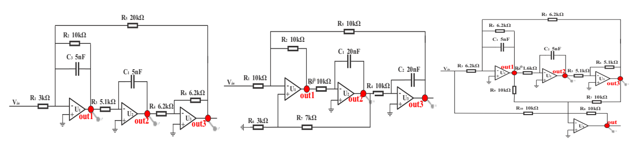
Supplementary Figures and Algorithms



(a) Relation transfer process (b) Data transfer process

(c) Task transfer process.

Fig. 1. Proposed solution.



(a) Tow-Thomas (b) CSTV (c) four-op-amp biquadratic

Fig. 2. Schematics of the filter circuits for experiments.

Algorithm 1 Proposed Regularization Method

Input: Source domain dataset G_1 , target domain dataset G_2 .

Output: The regularized source domain dataset G_1 .

1: Get the maximum value list of each node data in G_2 :

$$List\_max1 \leftarrow G_2$$

2: Get the maximum value list of each node data in G_1 :

$$List\_max2 \leftarrow G_1$$

3: Normalize the node data of each directed graph in G_1 :

$$G_1 \leftarrow MinMaxScaler(G_1, List\_max2)$$

4: Copy and fill *List_max1* to the same length as *List_max2*.

5: Shuffle the expanded *List_max1* internally:

$$List\_max1 \leftarrow shuffle(List\_max1)$$

6: Obtain the normalized G_2^1 :

$$G_1 \leftarrow Regularization(List\_max1, G_1)$$

Algorithm 2 Proposed Transfer Data Filtering Method

Input: Source domain dataset G_1 , target domain dataset G_2 , training model GA^{2}E, number of source domain data *S*, number of samples selected *T*, total training epochs *E*, initialized *MSE_flag,* weight incentive coefficient *alpha*.
Output: The transfer dataset G_T .

1: Initialize the sample weights W^1 for the source domain dataset $G_1 : W^1 = (W_1^1, W_2^1, ..., W_S^1) \leftarrow W_i^1 = 1/S$ **for** $i = 1, ..., S$
2: for e=1, 2,..., *E* do
3: According to the sample weights W^e , select *T* data from G_1 and merge them with G_2 to form an expanded dataset G_3 .
4: Obtain the trained GA^{2}E for dataset G_3 :
$$GA^2E \leftarrow TRAIN(GA^2E, G_3)$$
5: Computing MSE_loss: $MSE\_loss \leftarrow GA^2E(G_2)$
6: if MSE_loss < MSE_flag:
MSE_flag = MSE_loss
$W_i^e = W_i^e \times alpha$
7: else:
$W_i^e = W_i^e / alpha$
8: end if
9: Update $W_i^{e+1} : W_i^{e+1} \leftarrow W^e / (\sum_{i=1}^{M} W_i^e)$
10: end for
11: Obtain the transfer dataset $G_T : G_T \leftarrow TOP(W^E, G_1, T)$