Data preprocessing using XWT and application of GANs for fault diagnosis of analog circuits

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***Abstract*—In this reflection paper of the paper 'Generative Adversarial Networks With Comprehensive Wavelet Feature for Fault Diagnosis of Analog Circuits' by Wei He et al., we give a brief introduction and necessary background information required to understand the paper. We then give a summary and review of the paper, demonstrating our understanding. Finally, we present our thoughts on potential future work, followed by this paper's conclusion.**

***Index Terms*—cross wavelet transform (XWT) , wavelet coherence , generative adversarial networks (GANs), data regularization, semi-supervised learning, Analog-circuit fault diagnosis**

I. Introduction

Much machinery today still uses analog circuitry and are more challenging to identify faults than digital circuits. Over time, every circuit degrades in performance and likelihood of failures increases. Due to factors like nonlinearity and tolerances, the analysis of system functioning for analog devices is quite complicated.
In data-driven approaches of fault analysis (others are model-driven or a combination of both) take large raw data and include feature extraction and fault pattern classification to output the fault. Many approaches have been taken like time-domain statistical analysis, frequency-domain spectral analysis and machine learning methods like SVM, KNN, etc. Deep learning has also been successful but has the problem of overfitting. Use of GANs can effectively cope with many practical problems such as small sample size, overfitting.
The flow of the proposed implementation is:

1) Preprocess the data:
    - Acquire labelled fault and correct signals
    - Find the XWT and WCS, where WCS is decomposed into real and imaginary part. Thus 3 feature matrices are obtained.
2) Train the GAN with these 3 feature matrices as the input. A classifier is used after the GAN which identifies whether a fault (or a specific fault) occurred or not.

II. Background information

In this section, the background theory is provided which is required to understand the paper.

A. Continuous Wavelet Transform

$$W^x(u,v) = \frac{1}{|u|^{1/2}} \int_{-\infty}^{\infty} x(t)\bar{\psi}\left(\frac{t-v}{u}\right) dt \tag{1}$$

where $\psi(t)$ is the mother wavelet and the overline represents operation of complex conjugate. In this paper, they have used the Morlet function, which is simply a Gaussian-windowed complex sinusoid, as the mother wavelet.

$$\psi(t) \triangleq \frac{1}{\sqrt{2\pi}} e^{-j\omega_0 t} e^{-t^2/2} \quad \longleftrightarrow \quad \Psi(\omega) \quad = e^{-(\omega-\omega_0)^2/2} \tag{2}$$

The authors have used this particular mother wavelet because of its better ability of accommodating various signals.

B. Cross Wavelet Transform (XWT)

$$\begin{aligned} &\mathrm{XWT}^{xy}(s,\tau) \\ &= \frac{1}{p_\psi} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} W^x(u,v) W^{y*}\left(\frac{u}{s}, \frac{v-\tau}{s}\right) \frac{du dv}{u^2} \end{aligned} \tag{3}$$

C. Wavelet Cross Spectrum (WCS)

$$C_{xy}(a,b) = S\left(C_x^*(a,b) C_y(a,b)\right) \tag{4}$$

$C_x(a,b)$ and $C_y(a,b)$ denote the continuous wavelet transforms of x and y at scales a and positions b. The superscript * is the complex conjugate, and S is a smoothing operator in time and scale. The wavelet cross-spectrum is a measure of the distribution of power of two signals.

D. Wavelet Coherence

Wavelet coherence is a measure of the correlation between two signals.The wavelet coherence of two time series x and y is:

$$\frac{\left|S\left(C_x^*(a,b)C_y(a,b)\right)\right|^2}{S\left(\left|C_x(a,b)\right|^2\right)\cdot S\left(\left|C_y(a,b)\right|^2\right)} \tag{5}$$

E. Generative Adversarial Networks (GANs)

GANs denote a class of machine learning algorithms which belong to the set of generative models. These fall in the unsupervised learning paradigm, which aims to learn the underlying structure of the distribution of the data provided. This allows them to generate "fake" data in the sense that they can synthesise data from the learned distribution.

A GAN consists of two neural networks called the Generator G and the Discriminator D. The generator tries its best to generate fake data by learning the distribution of the original data whereas the discriminator tries its best to distinguish the real and fake data. These twin networks are trained in a game theoritic fashion until the Nash equilibrium is attained.

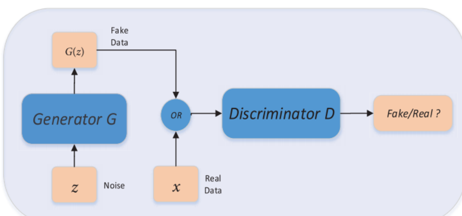

Fig. 1. Architecture of GAN [1]

A GAN is trained to solve the following minimax problem

$$\min_{\theta_g}\max_{\theta_d} V(\theta_d,\theta_g) = E_{x\sim p(x)}[\log(D(x))] + E_{z\sim p(z)}[\log(1-D(G(z)))] \tag{6}$$

where θ_g and θ_d are the parameters of G and D. Both G and D are trained using stochastic gradient descent. GAN is a potential choice because in many scenarios it is difficult to obtain large quantities of labelled data. Using a GAN we can synthesise data and train our model to avoid the problem of overfitting.

III. Summary and Review

The proposed fault diagnosis method is shown in figure 2. XWT spectrums of the fault signals are used as input to the GAN. A GAN with a slight modification is used to learn both discrimination of fake samples and multiclass classification. This has been trained using both the original data and fake examples. This section is organised as follows.

A. Data Preprocessing using cross wavelet transforms

The measured signals of the electronic systems are handled to obtain WCS and wavelet coherence (WCOH) ($C_{n\times m}$). The WCS matrices are complex valued and are decomposed into two matrices where one is composed of the real part($S^{real}_{n\times m}$)and the another the imaginary part($S^{img}_{n\times m}$). These matrices are now the input for the subsequent GAN.

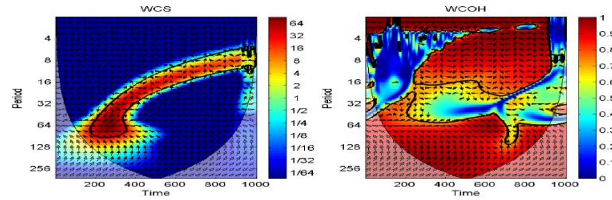

Fig. 3. WCS and Wavelet Coherence for biquad low pass filter [1]

We reflect upon why input was not taken to be just the experimentally obtained time-domain signal but processed to this from - The time domain representation is not always the best representation of the signal for most signal processing related applications. In many cases, the most distinguished information is hidden in the frequency content of the signal. Wavelet transforms are capable of providing the time and frequency information simultaneously, hence giving a time-frequency representation of the signal. This representation allows much more vivid discerning of the template (expected) and the fault signals and identifying specific faults is also easier. We also note that undesirable noise in the raw time-domain signal is also suppressed by using the wavelet transforms which is another benefit.

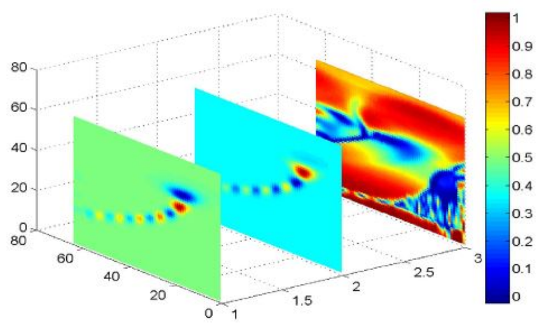

Fig. 4. The 3 input matrices corresponding to a faulty signal for biquad low pass filter circuit [1]

B. Classification by Modified GAN

The proposed method wishes to identify and classify different types of faults in the analog circuits, which falls in supervised learning paradigm. Although a GAN cannot be directly used for this purpose, a slight modification to the discriminator will serve the purpose. By means of semisupervised learning techniques, the discriminator D has been transformed into a classifier. The objective function of this GAN considers the probability of the right sources and the probability of the right class labels. While training this hybrid GAN, the objective

function consists of two parts, the log-likelihood of the right source of input data L_s and the log-likelihood of the right class

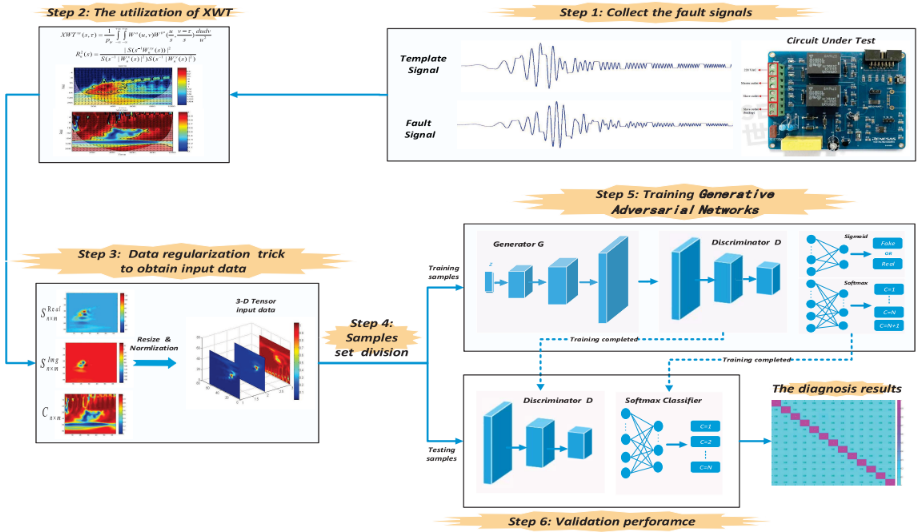

Fig. 2. Flowchart of the proposed method [1]

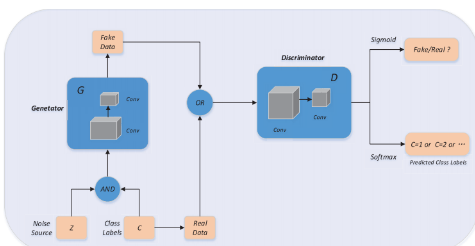

Fig. 5. Architecture of Proposed GAN [1]

label L_c given as

$$L_s = E[\log P(S = \text{real}|X_{\text{real}})] + E[\log P(S = \text{fake}|X_{\text{fake}})] \tag{7}$$

$$L_c = E[\log P(C = c|X_{\text{real}})] + E[\log P(C = c|X_{\text{fake}})] \tag{8}$$

The D is trained to maximize $L_s + L_c$ and G is trained to maximise $L_c - L_s$. As shown in figure 5, a softmax layer is used for multiclass classification and a sigmoid layer is used to discriminate real and fake data. It is worthy to note that the fake data generated by G is used only during training and not while testing. Testing is done by using D and the softmax layer on the real data. The sigmoid function σ and softmax function function ς are as follows:

$$\sigma(z) = \frac{1}{1 + \exp(-z)}, \quad \sigma : \mathbb{R} \to \mathbb{R} \tag{9}$$

$$\varsigma(\mathbf{z})_i = \frac{\exp(z_i)}{\sum_{k=1}^{N} \exp(z_k)}, \quad \varsigma : \mathbb{R}^N \to \mathbb{R}^N \tag{10}$$

While performing experiments, different activation functions and different batch normalization layers have been used to learn the inherent nonlinear dependencies robustly.

C. Experimental Results

For testing this proposed method, the authors took two circuits, biquad low-pass filter and Sallen–Key bandpass filter. Faulty components are intentionally introduced in both circuits to generate responses under the fault-free and fault conditions. Fault classes are defined according to the parameter deviation of different faulty components. The dataset consisting of the fault-free and the faulty responses was divided into training and testing dataset. Then the GAN model is trained using these samples to learn the features. As compared to other diagnosis methods which used methods like CNN, KNN, SVM etc. it performed better by 1% - 6%. The average accuracy is over 98% for the two circuits taken and increases with more training samples.

ARCHITECTURES OF THE PROPOSED GAN

Nets	Layer Number	Convolution Size	BN	stride	Padding	Activation function
G	1	$4 \times 4 \times 512$	Y	1	0	ReLU
	2	$4 \times 4 \times 256$	Y	2	1	ReLU
	3	$4 \times 4 \times 128$	Y	2	1	ReLU
	4	$4 \times 4 \times 64$	Y	2	1	ReLU
	5	$4 \times 4 \times 3$	N	2	1	Tanh
D	1	$4 \times 4 \times 64$	N	2	1	LeakyReLU
	2	$4 \times 4 \times 128$	Y	2	1	LeakyReLU
	3	$4 \times 4 \times 256$	Y	2	1	LeakyReLU
	4	$4 \times 4 \times 512$	Y	2	1	LeakyReLU
	5	$4 \times 4 \times 64$	N	1	0	N
	6	$64 \times n\_class$ 64×2	N N	- -	- -	Softmax Sigmoid

Fig. 6. Detailed Architecture of Proposed GAN [1]

The tradeoff for the increased accuracy is the increased time cost with the average time cost to be significatly larger than the previously listed methods.
The accuracy and time cost for the Sallen-key band pass filter is:

Average Accuracy(%)					
98.30	98.33	98.94	99.78	99.83	100
Average Time Costs(s)					
172.91	184.37	188.39	212.06	218.48	233.37

Fig. 7. Accuracy and time cost for the Sallen-key band pass filter

D. Further Work Possible

The proposed method uses the Morlet function as the mother wavelet. The paper mentions that the redundant property of XWT generates a bit of useless information which lead to misdiagnosis. Other wavelet functions can be used to see if better results can be obtained. The proposed method also uses vanilla CNNs for the generator and discriminator. Recent advances in the field of deep learning have brought many different new and fast architectures like Residual Networks (ResNet) and new learning paradigms like Few Shot Learning (FSL) into light. Using these architectures for the generator and discriminator will help in faster training and faster testing. Recently deep learning libraries like PyTorch and Tensorflow have been developed which make use of parallel processing and GPUs. This helps in speeding up model training and easy monitoring of the training process.

IV. Conclusion

This paper includes some extra and more complete background information for students still learning about wavelets which is assumed to be known in the original paper. This paper also tries to explain the choices made for the proposed method wherever possible and a summary of the implementation and results is presented. Future work to improve upon the existing method has been furnished.

References

[1] W. He, Y. He and B. Li, “Generative Adversarial Networks With Comprehensive Wavelet Feature for Fault Diagnosis of Analog Circuits,” in IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 9, pp. 6640-6650, Sept. 2020, doi: 10.1109/TIM.2020.2969008.
[2] Wavelet Coherence and Cross-Spectrum

V. Author Details and Brief Background

Mantri Krishna Sri Ipsit is a junior undergraduate pursuing Bachelor of Technology from the Department of Electrical Engineering at Indian Institute of Technology Bombay, Mumbai. He will be receiving his BTech degree by May 2022. His research interests lie broadly in the field of information technology specifically in signal processing and machine learning.

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