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Complex-Valued-Autoencoder for Structural Health Monitoring with Frequency Modulated Continuous Wave Radar

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Frequency Modulated Continuous Wave (FMCW) radar is a low power, compact mechanism which can be used for non-destructive health monitoring and inspection of surface and subsurface materials. It enables the detection of defects that are internal to the analyzed structural element and not visible from the surface. The key benefits of this technology are that it offers a non-contact monitoring tool at reduced costs, risk and duration of inspection. Although a recent study proposed the use of FMCW radar sensing for composite material characterization, it has not yet been applied to the context of health monitoring. In this work, we propose to study the feasibility of FMCW radar to detect anomalies in monolithic surfaces. We propose to consider the analytic representation of the difference between the emitted signal and the incident wave to limit the interferences between the echo delay and gain difference between both signals. From a methodological perspective, we propose a complex-valued-AutoEncoder (AE) with a new activation function. We compare the proposed methodology to other state of the art methods.

Keywords: FMCW Radar, Non-Destructive Evaluation, Complex-valued Autoencoder, Anomaly Detection, Analytical Representation.

1. Industrial context

Inspection during the manufacturing process is essential to ensure that composite materials are fabricated consistently. As a result, there is a need for sensing technologies that can detect anomalies in this high-quality material. Although there are various methods of inspection currently available or being developed for structural health monitoring in composites, embedding sensors during the curing process can potentially affect the curing process. Current research trends suggest a preference for non-contact sensing, such as Frequency Modulated Continuous Wave (FMCW) radar Tang et al. (2021). The aim of this study is to enhance the quality assurance of the manufacturing process by utilizing FMCW radar as a non-destructive tool. Thus, we propose a new anomaly detection methodology based on complex-valued residual AE applied to the analytic FMCW signal.

2. Method

We consider the experiment conducted in Tang et al. (2021). The raw data obtained from the microwave sensor consists of 1501 feature points acquired in 0.3 seconds in the time domain. This occur across a frequency sweep from 24-25-5 GHz. The signal output from the FMCW sensor is the Intermediate Frequency (IF), which is the difference between the emitted signal and the target interaction with the incident wave. We propose the analytical representation of the IF. The goal is to decompose the effect of the delay and gain between the emitted and incident wave into their phase and amplitude components, respectively, within the analytic representation. The analytic representation is computed as $\mathbf{x}^{\mathrm{H}} = \mathbf{x} + i\mathcal{I}[\mathbf{x}]$, where $\mathcal{I}[\bullet]$ is the Hilbert transform.

To perform anomaly detection based on the IF signals, we use an AE that is trained to reconstruct the healthy input only Chao et al. (2021). In the applciation phase, a decision on a newly measured sample is made based on the norm of its residual, which is the difference between the input and the output of the AE. An anomalous sample contains specific features that make it different from the healthy distribution, so it will not be reconstructed correctly by the AE and will have a high residual norm. The proposed AE contains an encoding network with two dense layers with 64 nodes, plus one of 32 nodes, while the decoder consists of two dense layers with 64 nodes. ReLU activation functions ($\mathrm{R}(x) = \max(0, x)$) are used after each layer, except the last one.

Regarding the analytic representation of complex values, denoted by $\mathbf{x}^{\mathrm{H}}$, a complex-valued AE is used. Considering the polar representation of a complex number $z = |z|e^{i\phi_z}$, where ϕ_z is the phase value, the two most common extensions of the ReLU layer for complex number are Bassey et al. (2021) $\mathrm{CR}_1(z) = \mathrm{R}(|z|\cos(\phi_z)) + i\mathrm{R}(|z|\sin(\phi_z))$ and $\mathrm{CR}_2(z) = \mathrm{R}(|z| - b)e^{i\phi_z}$, where b is a learnable parameter. In this work, we propose a new activation function called Exponential Amplitude Decay (EAD) and denoted by:

$$\mathrm{EAD}(z) = (1 - e^{-b|z|^2})e^{i\phi_z} \tag{1}$$

In addition to being differentiable, the activation function utilizes the assumed Rayleigh distribution of amplitude values in order to restrict the range of amplitude values to the unit circle.

3. Results

The 530 healthy samples are divided into three sets: training, validation and test, with a ratio of $[0.6, 0.2, 0.2]$. Only the test data set contains the 362 abnormal samples. For more details on the experiment conducted please refer to Tang et al. (2021). In order to establish the threshold that distinguishes between healthy and abnormal samples, based on the residual magnitude, we select the uppermost value, such that 95% of the samples in the validation dataset are considered healthy.

In Table. 1, complex-valued AE with CR_1, CR_2 and the proposed EAD activation function, as well as the real-valued AE using the IF signal, are compared. Additionally, we consider other unsupervised anomaly detection methods like K-Nearest Neighbors using (KNN), isolation Forest (iForest), DeepSVDD, Local Outlier Factor (LOF). The scores used for comparison are the average F1 score, accuracy and Area Under the Curves (AUC) over a 5-fold cross validation experiment, where our proposed approach outperformed the other methods.

Table 1. Anomaly detection performances of different methods. (Acc.= Accuracy score).

Method	F1	Acc.	AUC
cAE EAD	**0.94**	**0.91**	**0.978**
cAE CR_1	0.93	0.90	0.973
cAE CR_2	0.88	0.88	0.96
AE	0.91	0.89	0.970
KNN	0.90	0.85	0.972
LOF	0.90	0.86	0.970
iForest	0.70	0.64	0.90
SVDD	0.76	0.82	0.90
DeepSVDD	0.72	0.66	0.81

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