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Development of an Intelligent Failure Analysis System Based on Infrared Thermography and Finite Element Modelling Supported Data Augmentation for Deep Learning

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ABSTRACT

1. BACKGROUND

Defect detection in the manufacturing processes is pivotal for the modern industry. The demand for defect-free production is fuelled by the increasing complexity in manufacturing components and their application to critical tasks such as autonomous driving, space, healthcare, and many others. Inspecting defects via manual, visual evaluation via humans is subjective, time-consuming, might not consistently meet stringent quality requirements and not to forget the intensive training required in the first place. Different algorithms for defect detections in thermal images were proposed beginning from the 1990s. A comprehensive description and comparison of these classical techniques are provided in [1]. However, the application of these classical techniques for inline testing never saw the day of light due to the lack of a robust automation process. However, in the last decade, the advancements in deep learning algorithms coupled with powerful Graphics Processing Units (GPU) led to accelerated development in computer vision problems. The solution to object detection, image classification, and semantic segmentation is of great interest to the industry. The application of these advancements can be seen in [2], where the authors use a Faster Region-Based Convolutional Neural Network (R-CNN) network for crack detection in steel plates. Debonding and delamination are some of the most common defects in manufacturing, and research is being done to detect these defects using a hybrid of spatial and temporal deep learning [3]. The need for a completely automated process is further motivated in industrial processes in confined environments that are only observable by sensors [4]. A comprehensive review of modern defect detection models is provided in [5]. The major problem associated with the deep learning approach is the lack of data in the training set. The performance of the model is dependent on the quality and quantity of the training data. The training data should be a good representation of the real-world scenario, i.e. it should be accurate enough and contain enough images, including exceptions for learning reliable features. However, getting enough data is a challenge in the manufacturing industry. Currently, one of the main focuses of research is to overcome this data challenge with the help of synthetic data generated using Finite Element Modelling (FEM) [6, 7].

This work aims to build upon the concept of the use of synthetic data to aid learning of the neural network by not limiting the use of FEM just for the simulation of the actual fabricated samples but also to generate a feature-rich dataset that encompasses the variability of the real-world applications. The real-world variability is achieved by randomizing the parameters such as defect size, depth, location, material properties, excitation intensity in the FEM models. The FEM model will also help understand the influence of different features in the neural network's learning process. Furthermore, recent developments in computer vision research have led to some promising models such as Visual Transformer (ViT) [8] and TransUNet (Transfer and UNet) [9], which will also be explored along with traditional image segmentation models.

2. METHODOLOGY

Detection of buried defects in the specimen can be achieved using pulse thermography which combines light and thermal imaging technology. When uniform light is flashed on the surface of the specimen, radiation is absorbed by the specimen as heat. If there are buried defects in the specimen, the heat distribution at the surface of the specimen will be uneven due to the direct reflection of heat waves from the buried defect to the surface. The temperature evolution at the surface of the specimen is recorded using an infrared camera. To detect defects in the specimens, we use TIFAS® IR by Berliner Nanotest und Design GmbH, an all-in-one system for failure analysis using IR thermography. Developing an intelligent failure analysis system using deep learning can be briefly divided into four steps:

Step 1: Data generation

To achieve a specific goal (in this case, defect detection) using neural networks, sufficient data is needed to train and evaluate a neural network. Generating the required data just by experiments alone is expensive and time-consuming. The aim is to create a training dataset consisting of (a) *simulated data* from FEM with boundary conditions similar to the experimental setup and (b) the *actual experimental data*. Various samples for experiments and simulations are made from materials with different thermal properties. Given a range of allowed defect diameters and depths, one can create a permutation of defect profiles (defect of diameter φ at depth d) encompassing all the possible combinations of defects. Samples are fabricated and simulated by randomly selecting a defect profile and placing it randomly on the sample. Using FEM also enables us to generate samples with different material properties, defects of different shapes and sizes at different depths, and the excitation source's energy. Thus, the described approach will help in creating an inclusive dataset.

Step 2: Data pre-processing and preparation

The raw thermographic data provides all the information about the defects, but in some cases, with a low signal-to-noise ratio. In this regard, a post-processing algorithm is necessary to improve the quality of the results. Pulse Phase Thermography (PPT), Thermal Signal Reconstruction (TSR), and Principal Component Thermography (PCT) are most often used. The next step is to divide the measurement data into a training set for training the neural network and a test set to examine the trained neural network.

Step 3: Training of neural networks

During the neural network training, a loss function that compares each output image pixel with the corresponding pixel in the ground truth image is minimized. Once trained, the performance of the network is evaluated using the test set data. Techniques like data augmentation and grid transformation are helpful to avoid the problem of overfitting, and a limited dataset is compensated using the concept of transfer learning. Various neural network models are under consideration to make the most out of the available spatial and temporal data. Spatial data-based models like VGG-Unet, Mask-RCNN for image segmentation and temporal data-based models like LSTM is considered along with new models such as ViT and TransUNet.

Step 4: Performance evaluation

Different neural networks will be evaluated based on precision, probability of detection, loss per epoch.

3. <u>RESULTS</u>

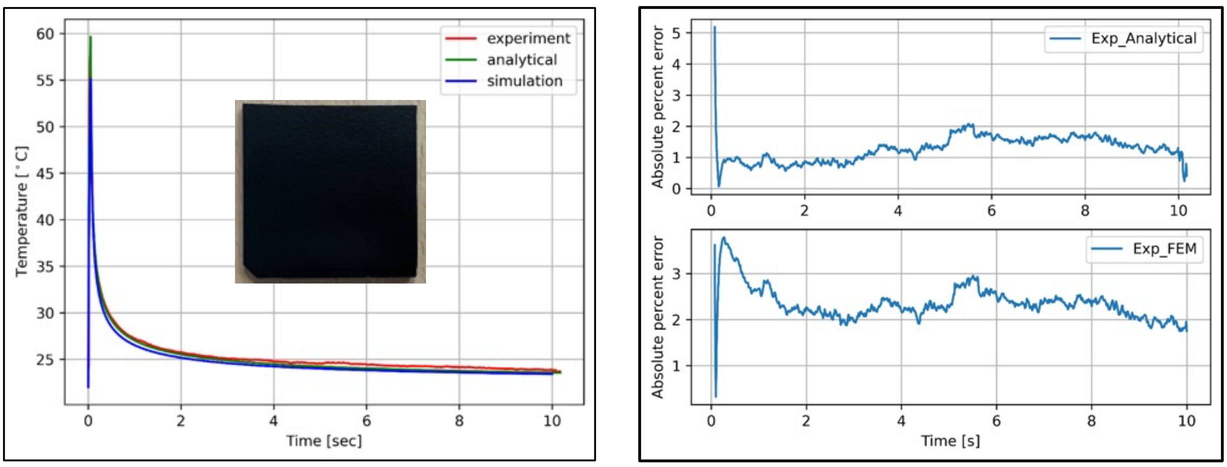
Step two has already been completed from the four steps explained in the methodology section [1]. Currently, step 1 is in progress. Randomized generation of defects on a sample is achieved with the help of a python script, and these samples are analysed using FEM. Finding the boundary conditions for the FEM is an iterative process with a feedback loop between experimental results and boundary conditions. The initial results comparing analytical, experiment and FEM curves are shown in Figure 1. Figure 1.a shows the temperature profile of the top surface for experimental, analytical and simulation. The analytical curve was obtained using the following equations [10]

$$\mathrm{T}(0,\mathrm{t}) = T_0 + \frac{2\mathrm{q}''}{\mathrm{k}}\left(\frac{\alpha\mathrm{t}}{\pi}\right)^{\frac{1}{2}}, 0 < t < \tau,$$

$$T(0,t) = T_0 + \frac{2\mathrm{q}''}{\mathrm{k}}\left(\frac{\alpha}{\pi}\right)^{\frac{1}{2}}\left\{\mathrm{t}^{\frac{1}{2}} - (\mathrm{t}-\tau)^{\frac{1}{2}}\right\}, \tau < \mathrm{t} < \mathrm{T},$$

where T (0, t) is the surface temperature at time t, q'' is the heat flux [W/m^2], τ is the heat pulse duration [s], α is the thermal diffusivity [m^2/s] and k is the thermal conductivity [W/(m K)]. Figure 1.b shows the absolute percentage error for the cooling curve of the experiment and analytical (Exp_Analytical) and experiment and FEM (Exp_FEM).

The paper will further explore in detail the pipeline of data generation and its integration in the deep learning network, the error in the surface temperature estimate for a sound and defect area for experimental and finite element model, use of optimization loop to extract the boundary conditions from the experimental data for the finite element modelling, use of axis-symmetric models to reduce the computational time for the transient thermal simulations and the results of different neural network models on the generated dataset.



(a) (b)

Figure 1. (a) Top surface temperature profile for experimental, analytical and simulation, (b) absolute percentage error.

4. References

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