Surface Damage Identification in 3D Printed Metal Parts Using Convolutional Neural Network

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ABSTRACT

Surface Response to Excitation (SuRE) is an active Structural Health Monitoring (SHM) method used in this study for the detection and quantification of the artificial damages created by the milling operation on additively manufactured metal plates. In this method, one piezoelectric element is bonded to one end of the test specimen to excite it with surface waves and the dynamic response to excitation is recorded by another piezoelectric at the other end of the part. The excitation signal is a sweep sine wave with a duration of 1 ms and a frequency range of 50-120 kHz. Using a Markforged metal 3D printer, five stainless steel plates of identical size (195×54×2.5 mm) were created. The data was recorded when all the parts were in a healthy condition and when they were face milled at 3 different lengths. The collected sensory data in the time domain were converted to time-frequency representation images using continuous wavelet transform (CWT). Different data augmentation methods have been implemented for expanding the size of the dataset. The image dataset was used as input to train a Two-Dimensional Convolutional Neural Network (2D-CNN) for the detection of damage and also for quantifying the damage length. The CNN could detect the damaged parts with 97.4% accuracy and classify the damage length with an overall accuracy of 98.7%.

INTRODUCTION

Additive manufacturing (AM) technology enables the creation of complex parts and allows for more control of internal features such as infills and skin thickness which is not possible with traditional manufacturing methods. The advantages of AM are low manufacturing costs, material and energy savings, printing assembly as a single item, and no tooling expenses [1, 2]. One of the most popular AM methods is fused filament fabrication (FFF), also known as fused deposition modeling (FDM).

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Repetitive patterns known as infills, which can be used to define the internal geometry of additively manufactured objects, can help reduce weight, material, and manufacturing time [3]. Direct metal laser sintering (DMLS) was the first method of metal 3D printing that was patented in the 1990s. Four of the most widely utilized metal 3D printing technologies are Powder Bed Fusion (which includes Selective Laser Melting (SLM) and Electron Beam Melting (EBM)), Direct Energy Deposition (which includes Laser Material Deposition (LMD), and Electron Beam Additive Manufacturing), Binder Jetting, and Bound Powder Extrusion [4, 5].

Due to the rising demand for employing AM parts in many engineering fields, it is necessary to develop structural health monitoring (SHM) systems for evaluating the structural integrity and damage detection in these parts [6, 7]. In order to track various structural flaws, SHM methodologies use different damage identification techniques which need to be applied with appropriate modifications for small AM parts [8]. Surface Response to Excitation (SuRE) is a cost-effective active SHM method that has shown successful applications for the detection of loose bolts, delamination in composite plates, and compressive loading on the structures [9, 10]. In this method, one piezoelectric is attached to the host structure as an actuator for exciting the part with ultrasonic surface waves, and one/multiple piezoelectric(s) are used for monitoring the dynamic response to excitation at desired locations. Any changes in the mechanical properties of the structure or the loading conditions can be reflected in the monitored sensor signal. In this study, the effectiveness of the SuRE method is assessed in terms of its ability to identify and categorize damages (simulated by machined slots) on additively manufactured metal parts.

Due to the need for continuous monitoring of the structural condition, handling high amounts of data requires employing data-driven approaches. In classical machine learning, feature extraction and feature selection process should be done manually, while deep learning algorithms such as convolutional neural networks (CNN) have automated this procedure. Elforjani et al. [11] used artificial neural networks (ANN) and support vector machine (SVM) for feature extraction from AE signals for damage detection in ball bearings. In a Finite Element analysis, Gulgec et al. [12] used CNN for damage detection and localization.

In this study, four stainless steel plates have been manufactured with the same geometry (195×54×2.5 mm) and manufacturing condition using a metal 3D printer. Two piezoelectric disks were permanently attached to each end of the parts for surface wave excitation and monitoring the dynamic response to excitation. The data was recorded when each part was in a healthy condition without any surface damage and when a slot was machined at the center of each specimen at three different lengths (10mm, 25mm, and 40 mm). For each of these four circumstances, the data was recorded twice when one PZT played the role of a sensor and the other was used as an actuator, and vice versa. Implementing the Continuous Wavelet Transform (CWT) scalogram images of the recorded data were obtained and used as the input image dataset for training 2D-CNN to detect the surface damages and categorize the length of the damage.

EXPERIMENTAL SETUP

Manufacturing Process

All four test specimens were made using 17-4 PH stainless steel filament on a Markforge Metal X System 3D printer. Atomic Diffusion Additive Manufacturing (ADAM) is the manufacturing process used in this printer which is an extrusion-based technique to create parts layer by layer from a filament that is composed of a wax binder and metal powder mixture [13]. To remove the polymer binder and get the desired mechanical characteristics, post-processing procedures are required. Opteon SF-79, a high-performance solvent, is used to wash parts to remove a significant amount of the binder. The part is then given a heat treatment in the sinter using a mixture of hydrogen and argon gases, allowing it to achieve its final dimensions, purity, and mechanical properties. As part of the sintering process, the pieces are heated to roughly 85% of the metal's melting point, converting them from a loosely bonded metal powder (referred to as the brown part) to a fully metal portion (referred to as the green part) [14]. Figure 1 shows the workflow of the Markforged metal 3D printer.

Test Setup

Figure 2 shows damage creation on one of the test specimens by milling the surface of the part. Figure 3 illustrates the experimental setup used in this study. Two piezoelectric disks (SMD10T04R111WL) were permanently attached to the test specimen at its opposite ends. A sweep sine wave in the range of 50 kHz to 120 kHz was produced using an arbitrary function generator (Rigol DG1022) with a 20 V peak-to-peak amplitude and a 1 ms sweep period. A digital oscilloscope (Owon XDS3104AE) with a 25 MS/s sampling rate is used to record the response to excitation. The response of the specimen was recorded when the part was in a healthy condition and when it was surface machined with a slot having 2 mm width and 3 different slot lengths (10, 25, and 40 mm).

Continuous Wavelet Transform (CWT) was utilized to transform the recorded sensory data in the time domain into time-frequency representation images called scalograms. Short-Time Fourier Transform (STFT) is another algorithm used in the literature for presenting a signal in the time-frequency domain. The advantage of CWT over STFT is its variable time-frequency resolution instead of a fixed resolution. STFT uses a fixed time window while in the CWT the window will be shorter during the high-frequency area and longer during the low-frequency area. The obtained scalograms are saved as an image datastore for training CNN. In this study, the classification of the recorded data was done using a two-dimensional CNN. The dimensions of the input images were $680 \times 600 \times 3$ in width, height, and color channels (red, green, and blue), respectively. The architecture of CNN used in this study is shown in Figure 4. It consists of three main layers, an input layer, an output layer, and multiple hidden layers. The hidden layers are responsible for feature extraction and consist of blocks of the convolutional layer and pooling layer. In the convolution layer, different filters are applied to the input data which results in the reduction of the width and length of data while increasing its depth.

Rectified Linear Unit (ReLU) is the activation function added after the convolutional layer in each block for bringing non-linearity into the network. Stochastic gradient descent with momentum (SGDM) is the optimizer used in this study with an initial learning rate of 0.001. The number of epochs was set at 50. The number of filters in Convolution layers 1, 2, and 3 are 16,32, and 64, respectively. Max pooling with a stride of 2×2 is selected for the pooling operation.

Figure 1: workflow of the Markforged metal 3D printer.

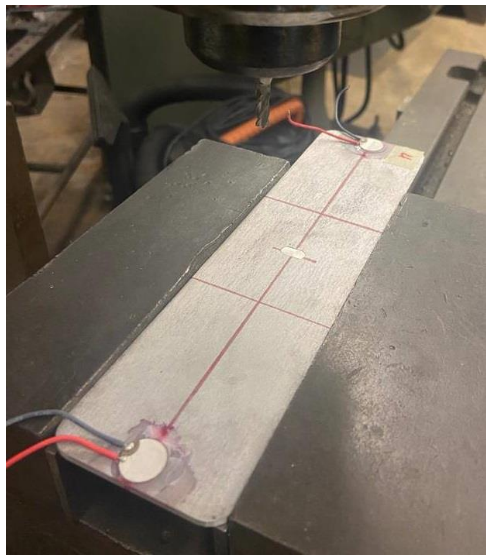

Figure 2: Test specimen

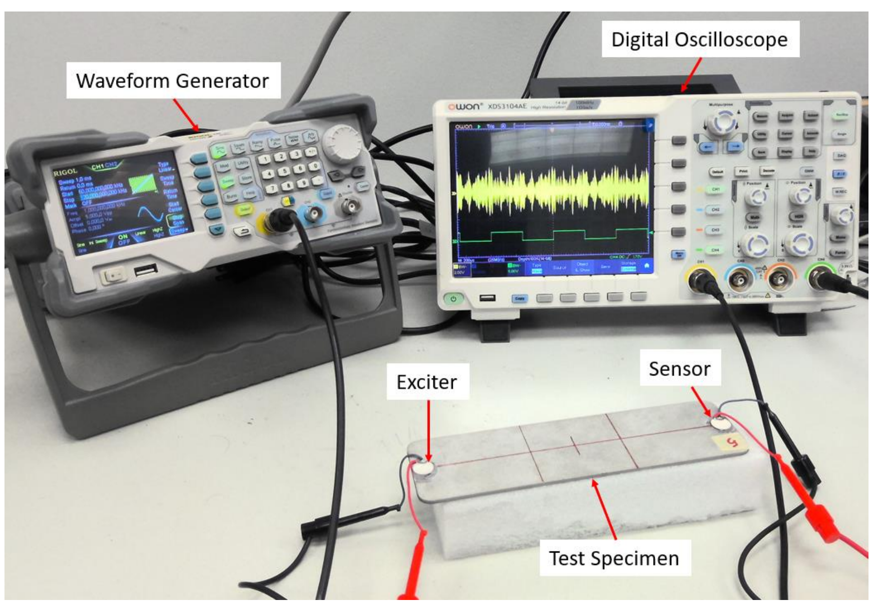

Figure 3: Experimental setup

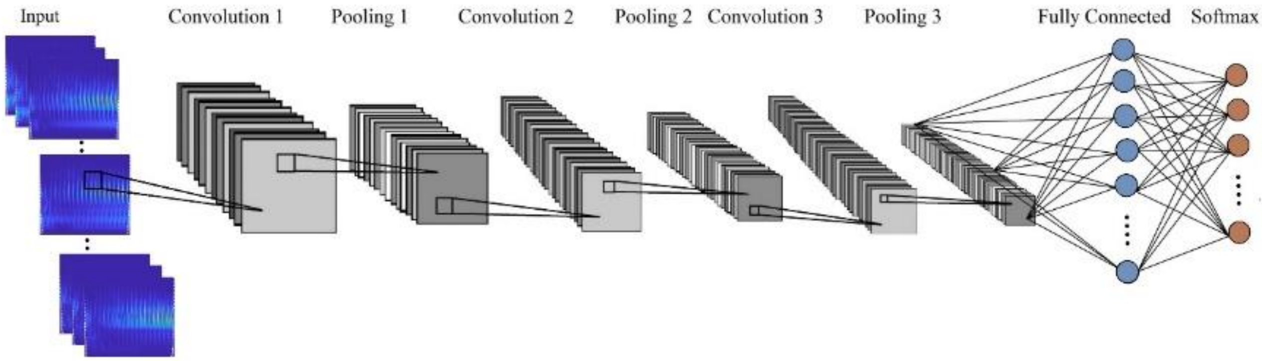

Figure 4: CNN architecture

RESULTS

Figure 5 shows the recorded data in the time domain for each test case. The CWT scalogram of the sensor data are presented in Figure 6. As can be observed in the scalograms, the most meaningful information is in the frequency range of 30-200 kHz. So the scalograms are cropped in this range to carry the most informative sections for training the network. Data augmentation (DA) is a technique used to generate new data when there is not enough data by artificially generating new data based on existing training data. Training the model on more diverse samples makes it more robust and invariant to transformations that it may encounter when generalizing to unknown samples. Using a more comprehensive set of data, data augmentation can minimize the distance between training and test datasets to solve overfitting. Three data augmentation methods have been applied to the time-series data in order to increase the size of the dataset. Adding Gaussian white noise with a signal-to-noise ratio (SNR) of 15, denoising, and scaling the signals with 0.9 and 1.1 factors. Figure 7 shows the augmented data obtained from the raw time-series data.

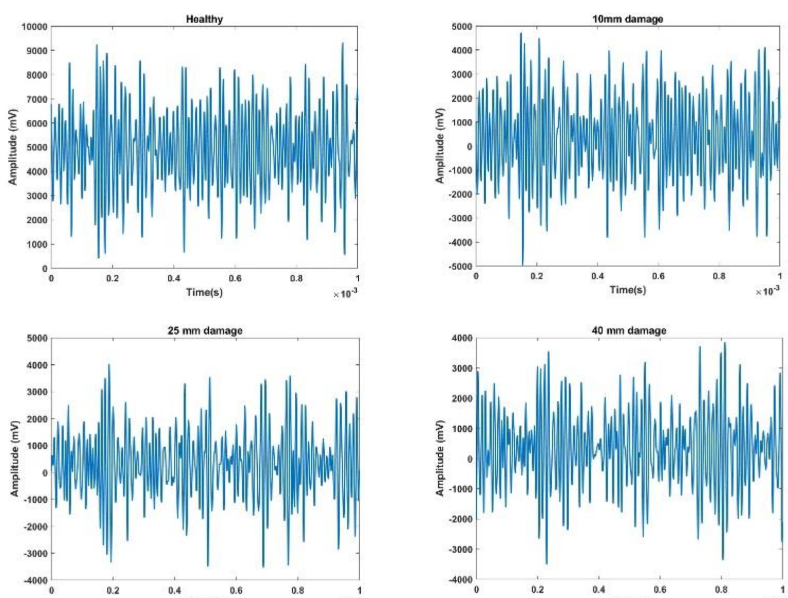

Figure 5: Time domain response of the recorded data

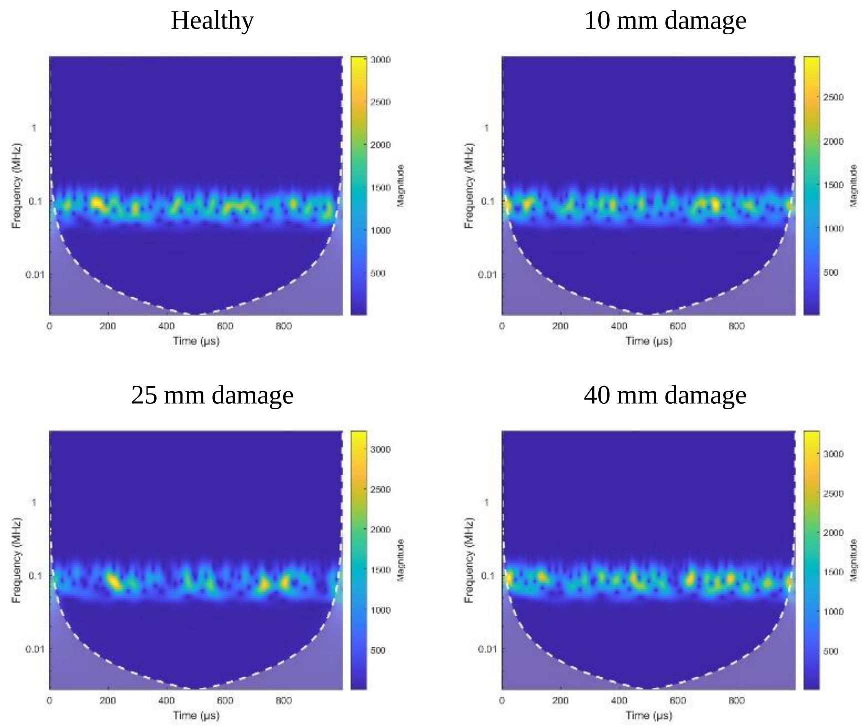

Figure 6: Scalogram of the response data for each case

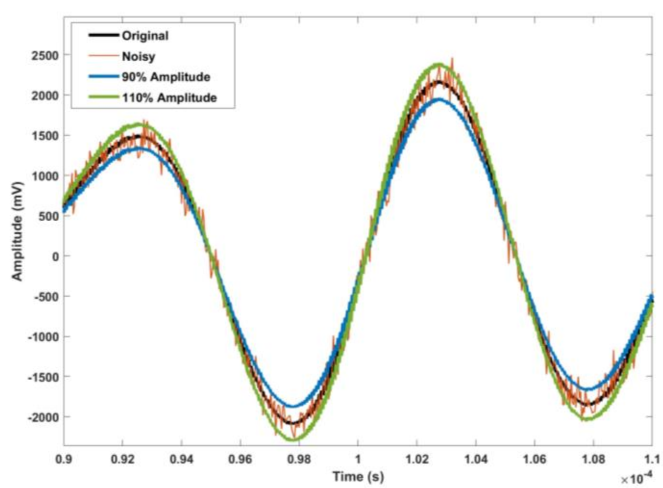

Figure 7: Augmented data in the time domain

The image datastore has been categorized to perform two studies for damage detection and damage identification. In the first study, CNN was employed for the binary classification of healthy and damaged cases. The number of damaged cases is three times higher than the number of healthy cases. The results show that CNN could detect the existence of damage with 97.4% accuracy. Figure 5 shows the confusion matrix for the first study. In the second study, CNN was used for the classification of damage length. There are four classes; Healthy part, 10 mm, 25mm, and 40 mm long damage. The overall accuracy of the classification was 98.7% with only one case of healthy misclassified as the parts with the smallest damage. In both studies, the data was split into 70% and 30% for the training and testing of the network, respectively.

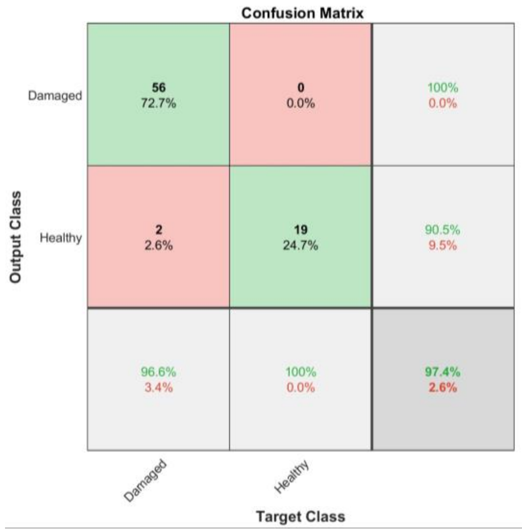

Figure 8: Confusion matrix for damage detection

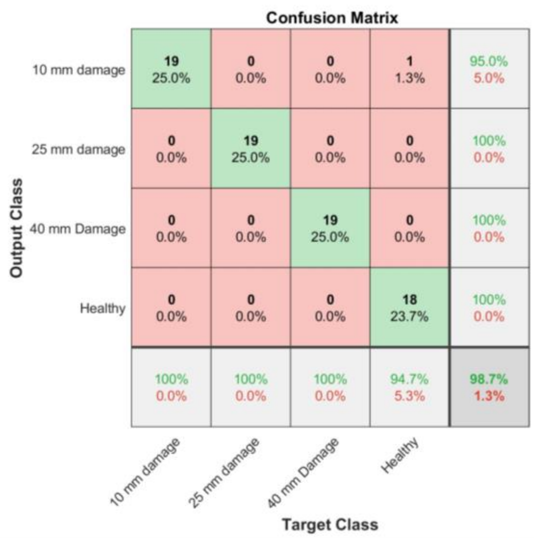

Figure 9: Damage length classification results

CONCLUSION

Application of the additively manufactured metal parts is increasing rapidly in different engineering sectors for the fabrication of complex components. In this study, Two-Dimensional Convolutional Neural Networks (2D-CNN) was implemented for damage detection and damage evaluation in 3D-printed metal plates. The Surface Response to Excitation method was used for exciting the parts with surface wave ad monitoring the dynamic response to excitation. The sensor data was collected when the parts were in a healthy condition and when deliberate damages were simulated on the surface of the parts using a milling machine. Data augmentation methods were used for increasing the size of the dataset. CWT was used for converting the time-series data into scalogram images for feeding into CNN as input data. The classification results show that CNN could distinguish between healthy and damaged parts with 97.4% accuracy. The trained network could estimate the length of the surface damage with 98.7% accuracy which shows the proposed method is a reliable technique for damage detection as well as damage identification in 3D printed components.

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