Chapter 6
Damage Assessment with Laser Ultrasonics in 3D-Printed Plate

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Abstract The growing use of 3D-printed (additively manufactured) structural components implies the need to develop effective methods of damage assessment. This study focuses on guided wave propagation and its interaction with structural damage. The waves were excited using a laser scanning system which allows for easy excitation of the waves at various points at the surface. Also, the excitation is broadband, giving the ability to excite more guided wave modes at once. The combined laser scanning with a single piezoelectric measurement transducer takes advantage of reciprocity to reconstruct the full propagating wavefield. The investigated sample was printed from an aluminum alloy. The first set of measurements was realized for an intact (healthy) sample. Next, an artificial damage was introduced in order to study the wave interaction with it. Machine learning-based signal process algorithms were developed to analyze the wave interaction with the damaged plate. The obtained results show a good potential of guided wave-based techniques for the structural health monitoring of 3D-printed structures.

Keywords Guided waves · Laser ultrasonics · 3D printing · Nondestructive evaluation · k-means clustering · Principal component analysis

6.1 Introduction

The growing use of 3D-printed (additively manufactured) structural components implies the need to develop effective methods of damage assessment. Structural health monitoring (SHM) and nondestructive evaluation (NDE) approaches are focusing on the evaluation of structural elements without causing any permanent alterations, and there is a need to develop tailored approaches to inspect additively manufactured structures. NDE is most prominent in industries requiring very detailed inspections of structures that survive long past the manufacturing process such as in aircraft [1] and nuclear power plants [2]. Such complex structures such as aircraft undergo a variety of loads continuously over time that may lead to structural deterioration and damage development. That may be often hidden or barely visible [3]. One prominent technique within NDE is the usage of laser ultrasonics to determine and estimate the structural health of materials [4]. Laser ultrasonics takes advantage of laser excitation of the guided waves, and the resulting data are analogous to that obtained by laser vibrometry, which was successfully applied to the inspection of printed samples in the past. The 3D-printed and traditionally manufactured aluminum plates were studied employing ultrasonic transducers and laser vibrometers with second-harmonic Lamb wave propagation [5]. The laser ultrasonic and laser vibrometry provide valuable insight into structural health monitoring due to scanning abilities providing high-resolution images produced from the wavefield data collected from its propagation throughout the material. Although this technique proves its value from the high spatial resolution data that it collects, the analysis of laser ultrasonics data requires specialized skills from knowledgeable experts to

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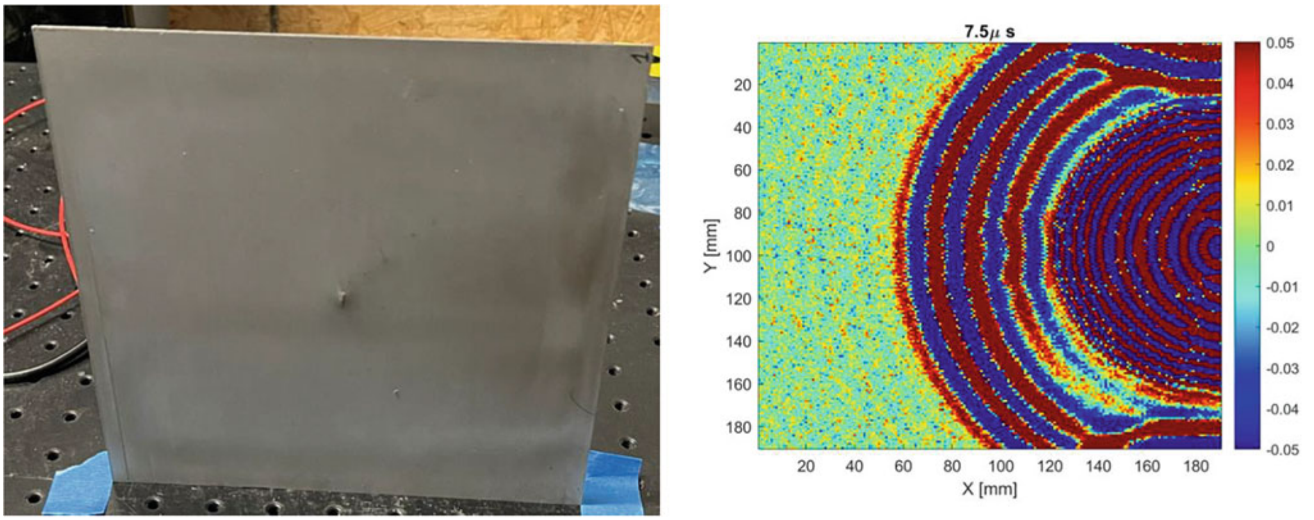

a) b)

Fig. 6.1 (**a**) View of the samples from the laser scanned side; (**b**) the registered guided wave propagation: Two wave modes are visible with different wavelengths

interpret them; in fact, this not only applies to laser ultrasonics but many advanced techniques in NDE as well where machine learning is currently being utilized to automate such processes [6]. In this paper, we propose a data handling procedure to improve the automatization of the damage assessment process in the printed aluminum plate with simulated damage. The gathered data are transformed using principal component analysis (PCA) to perform k-means clustering for the classification.

6.2 Experimental Setup

The study was performed using a laser ultrasonic integration system (LUIS) which comprises a laser scanning system, a data acquisition system, and a piezoelectric sensor. The laser scanning system incorporates a diode-pumped solid-state Q-switched Nd:YAG laser that was used for the wave excitation and a 2D laser mirror scanner to move the laser beam along a defined grid of points allowing for multiple excitation points. The investigated specimen (200 mm × 200 mm × 1 mm) was additively manufactured out of AlSi10Mg alloy. To collect the wavefield data from the surface of the plate, the contact sensor is mounted at its edge center using cyanoacrylate adhesive. The plate was firstly measured in a healthy state (intact), and later, a 10 mm × 1 mm notch was introduced to simulate damage that was next deepened (Fig. 6.1a). It was located in the middle of the plate with a longer edge parallel to the edge with the piezoelectric sensor. With this specimen, a raster scan across the surface was performed with the LUIS. At each designated scan point of the aluminum plate, the laser pulses, causing an ultrasonic wave to propagate symmetrically throughout the plate. The mounted piezoelectric transducer senses the energy from the surface of the plate and sends the measurements to the oscilloscope, where the data are digitized and read for a single point until every scan point is covered by the laser. The data that are collected by the oscilloscope are read as an $N \times M$ grid of points. Each of these points contains the time series data collected for that scan point. The entire wavefield data read in is represented as a three-dimensional image of the ultrasonic wave propagation with two spatial dimensions and one temporal dimension described as $N \times M \times T$. The registered data at one time moment are presented in (Fig. 6.1b).

6.3 Methodology

From the three-dimensional image that is collected from the LUIS, it is necessary to clean the data such that only the incident wave is visible; i.e., ambient noise from the start of the sensor recording and images including feedback from reflected waves after the incident wave has propagated throughout are discarded. This reduces the dimensions of collected LUIS data from $N \times M \times T$ to $N \times M \times T_{\mathrm{r}}$. From the time-reduced dataset, every spatial point (n, m), where $n \in N$, $m \in M$, is Fourier transformed such that the original dataset is transformed from $N \times M \times T_{\mathrm{r}}$ to $N \times M \times Lf$ where L_{f} is the corresponding

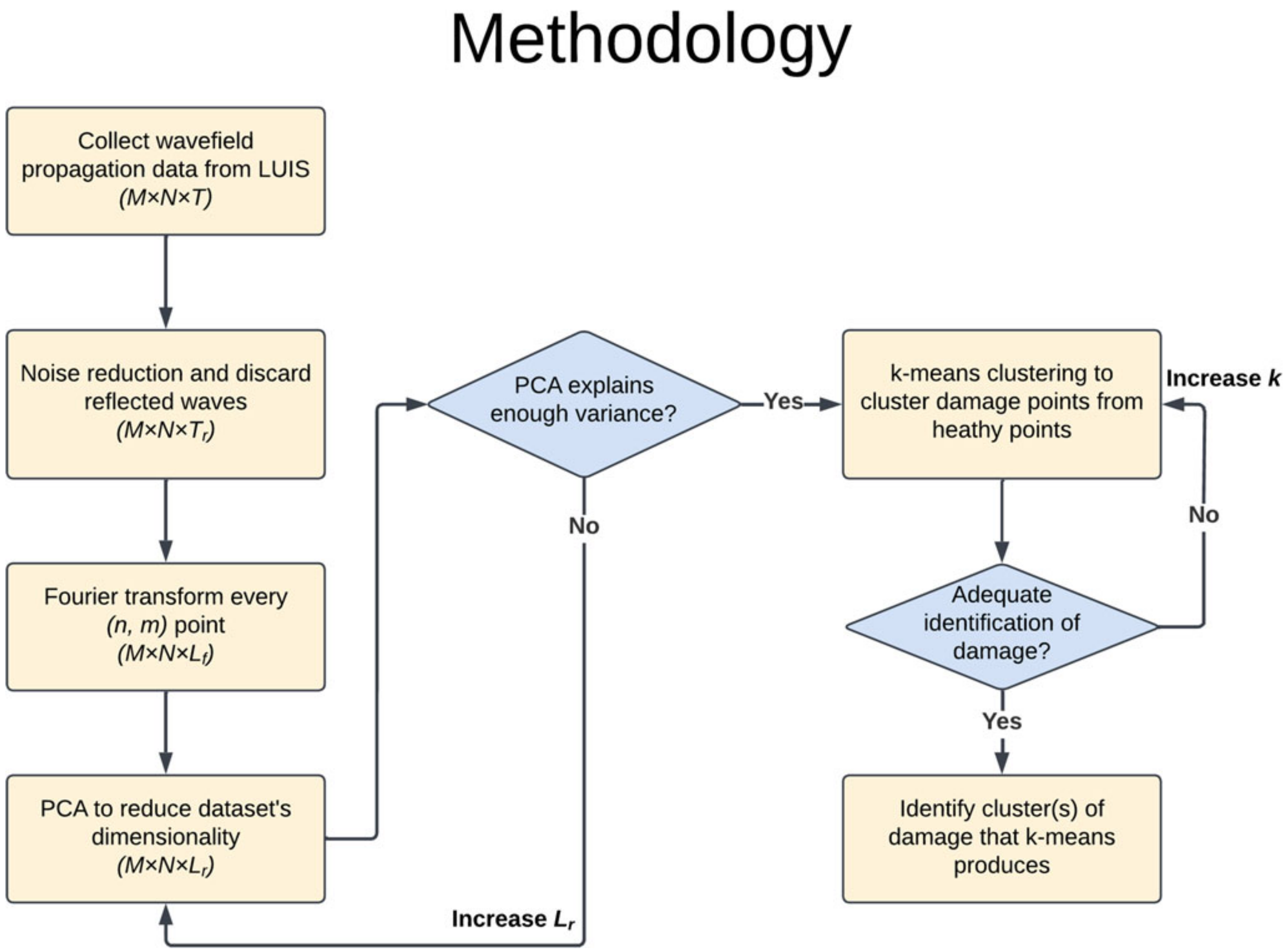

Fig. 6.2 Flowchart of the given methodology above

frequency space for each (n, m). To utilize the $N \times M \times L_f$ dataset of spectra that were generated from the Fourier transform of each (n, m), it is necessary to reduce the dimensionality of our dataset to increase the efficiency of any machine learning model using this dataset. This is the case since the clustering technique scales with the number of data points within the dataset, so reducing the dimensionality and losing information is the tradeoff for computational efficiency. To preserve the most information from the dataset while reducing many variables, principal component analysis (PCA) is used. In general, the $N \times M$ grid of scan points would be very large to maintain high spatial resolution data and L_f would vary depending on sampling frequency and speed of the wave propagation, so PCA will be very helpful in saving computational resources and runtime. PCA was used to compress the original Fourier transformed dataset such that $N \times M \times L_f \rightarrow N \times M \times L_r$, where L_r is the space of principal components used to explain L_f. Using the PCA-reduced dataset of size $N \times M \times L_r$, k-means clustering was performed. K-means clustering is an unsupervised machine learning algorithm that forms k clusters based on x number of observations in the dataset where x is $N \times M$ number of points scanned by the LUIS. Analyzing all k clusters, it is feasible to automate searching for the cluster that maintains the shape and information of the specimen's damage since, in general, $k \ll N \times M$. The workflow of the entire methodology is given in Fig. 6.2.

6.4 Results

After performing a scan of the aluminum plate, the dataset for both the deeper and shallow cuts obtained was a $190 \times 190 \times 500$ matrix. The reference, deeper, and shallow cut datasets are then reduced to $190 \times 190 \times 211$, $190 \times 190 \times 211$, and $190 \times 190 \times 231$, respectively, after cleaning the dataset of ambient noise and reflected waves. After computing the Fourier transform of every scan point, PCA is performed. Performing PCA on the dataset was able to reduce

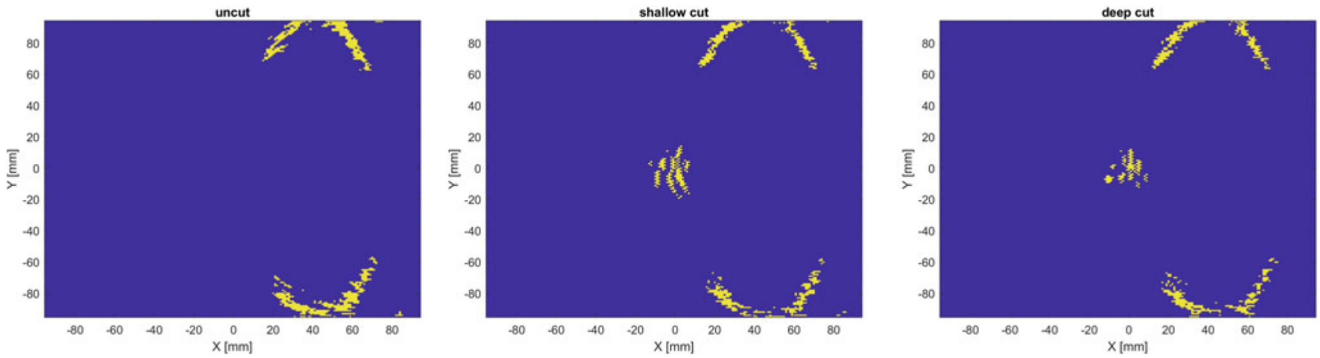

Fig. 6.3 Results of clustering; clusters indicating: (**a**) edges reflection (reference measurement); (**b**) damage reflection and edges reflection (measurement for shallow cut); and (**c**) damage reflection and edges reflection (measurement for deep cut)

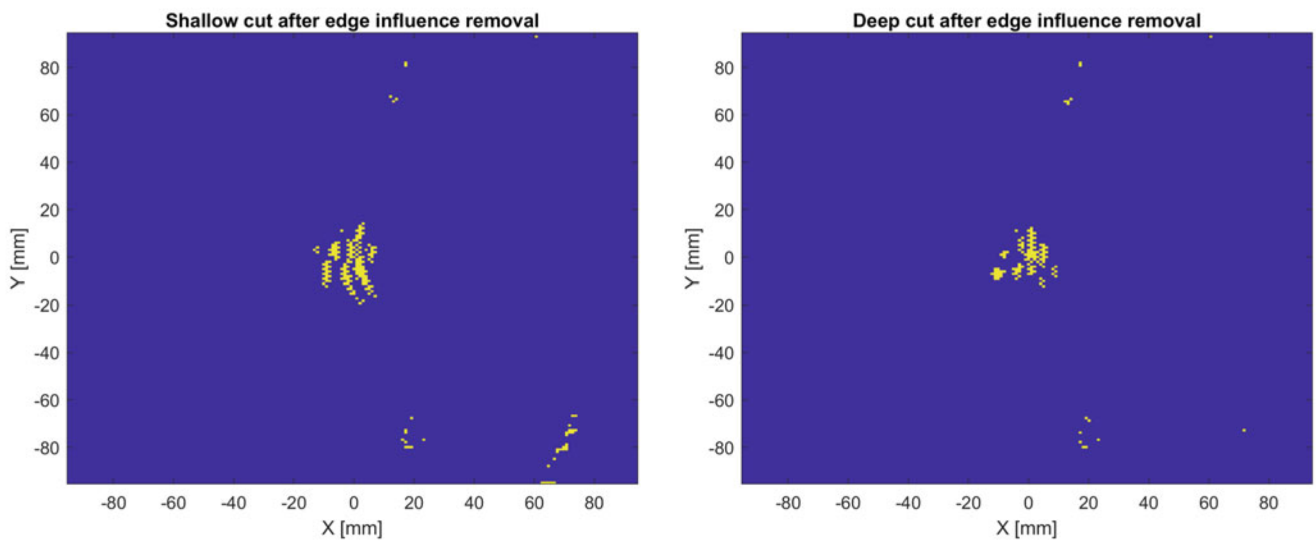

Fig. 6.4 Results after edge influence removal: (**a**) shallow cut case; (**b**) deep cut case

the dimensions of both datasets to merely 190 × 190 × 3. Here, three principal components explained approximately 92.79%, 92.86%, and 92.52% of the variance in the time-reduced datasets for the reference, shallow, and deeper cut, respectively.

With the PCA-reduced datasets, k-means clustering is performed. Naturally, as the number of principal components and number of clusters rise, computational workload increases and takes much longer to compute. However, since PCA was so efficient in reducing the dimensionality of the dataset, the result is a very efficient pipeline that clusters damaged points from healthy points. Experimentally, we determined that the optimal number of clusters to choose using three principal components for these datasets is $k = 50$ clusters.

We were able to highlight the cluster containing the damaged points in the scatter plot by manually plotting and visualizing every point. Cluster no. 36 indicated the damage location for the data for shallow and deep cuts (Fig. 6.3b, c), while the data used for reference were obtained from the 31st cluster (Fig. 6.3a). There is a large improvement in identifying the damage location on the aluminum plate. As opposed to analyzing 500 images per measurement, this procedure ensures that a clear image of the damage is guaranteed by searching through only 50 images.

Although the location of the damage is clearly indicated in both cases (shallow and deep cut), there is still an indication related to wave reflection from the top and bottom sample edges. It is the same as visible in the undamaged plate (Fig. 6.3a). Simple direct subtraction cannot remove this since the pixel locations representing edge reflection are a bit different in each of the cases, although the shape is similar. In order to facilitate the background subtraction, a numerical procedure was developed that assumes a ±3 mm margin (for X and Y) for subtraction and allows the removal of the edge influence almost completely (Fig. 6.4).

6.5 Conclusion

In this paper, a machine learning-based damage assessment of laser ultrasonic imaging data was proposed. The damage search is performed in steps, where the data undergo filtering, Fourier transform, PCA decomposition, and then k-means clustering to find the damage location. Although the identification of clusters for reference and with damage information was done manually, these steps may be automated. In the future, this procedure may be modified to work also for other materials (both printed and standard).

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