Second Annual Progress Report on Pulsed Thermal Tomography Nondestructive Examination of Additively Manufactured Reactor Materials

Pulsed Thermal Tomography Nondestructive Examination of Additively Manufactured Reactor Materials and Components

Nuclear Science and Engineering Division

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*Pulsed Thermal Tomography Nondestructive Examination of Additively Manufactured
Reactor Materials and Components*

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September 30, 2020

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Abstract

Additive manufacturing (AM) is an emerging method for cost-efficient fabrication of nuclear reactor parts. AM of metallic structures for nuclear energy applications is currently based on laser powder bed fusion (LPBF) process, which can introduce internal material flaws, such as pores and anisotropy. Integrity of AM structures needs to be evaluated nondestructively because material flaws could lead to premature failures due to exposure to high temperature, radiation and corrosive environment in a nuclear reactor. Thermal tomography (TT) provides a capability for non-destructive evaluation of sub-surface defects in arbitrary size structures. Thermal tomography is a computational method for heat diffusion-based imaging of solids, which provides 3D visualization of data from flash thermography measurements. We investigate thermal tomography imaging and nondestructive evaluation of stainless steel and nickel super alloy metallic structures produced with laser powder bed fusion (LPBF) additive manufacturing (AM) process. Metallic structures produced with LPBF contain defects, and there are limited capabilities to evaluate these structures non-destructively. Thermal tomography reconstruction of 3D apparent spatial effusivity provides information about AM structure geometry and internal material flaws. We study performance of thermal tomography in imaging of metallic structures through COMSOL computer simulations of transient heat transfer, and through reconstruction of data obtained from experimental measurements. Reconstruction of internal defects is investigated using a stainless steel 316L specimen with flat bottom hole (FBH) indentations, and Inconel 718 plate produced with laser powder bed fusion (LPBF) method, which contains imprinted hemispherical shape low density regions containing non-sintered metallic powder. The FBH's have the same sizes as the imprinted defects in the LPBF specimens, but offer better imaging contrast. Thermal tomography reconstructions provide visualizations of internal defects, and allow for estimation of their sizes and locations. Detection sensitivity of TT is limited by noises. We investigate separation of signal from noise in thermography images using several machine learning (ML) methods, including new spatio-temporal blind source separation (STBSS) and spatio-temporal sparse dictionary learning (STSDL) methods. Performance of the ML methods is benchmarked using thermography data obtained from imaging stainless steel 316L and Inconel 718 specimens produced LPBF method with imprinted calibrated porosity defects. The ML methods are ranked by F-score and execution runtime. Finally, we investigate TT of AM stainless steel 316L specimen with imprinted internal porosity defects using relatively low-cost, small form factor infrared (IR) camera based on uncooled micro bolometer detector. Sparse coding related K-means singular value decomposition (SVD) machine learning, image processing algorithms are developed to improve quality of TT images through removal of Additive white Gaussian noise without blurring the images. Following initial qualification of an AM component for deployment in a nuclear reactor, a compact TT can also be used for in-service nondestructive evaluation (NDE). With capability to perform in-service NDE of the AM component lifecycle, TT data can be used for development of a component *digital twin*.

1. Introduction

Additive manufacturing (AM) is an emerging method for cost-efficient production of low-volume custom and unique parts with minimal supply-chain dependence [1]. In particular, AM potentially provides a cost-saving option for replacing aging nuclear reactor parts and reducing costs for new construction of advanced reactors [2]. Metals of interest for passive structures in nuclear applications typically include high-strength corrosion-resistant stainless steel and nickel alloys, such as stainless steel 316/316L (SS316L) and Inconel 718 (IN718). Because of high strength (e.g. 205MPa tensile yield strength and 515MPa ultimate tensile strength for SS316L), shape forming of these metals into complex geometry structures is not trivial. AM of such metals, which have melting range 1370°C to 1430°C, is currently based on laser powder-bed fusion (LPBF) [3,4]. Schematics of LPBF process are show in Figures 1(a) and 1(b) [5]. Because of the intrinsic features of LPBF, e.g. Marangoni convection, material defects such as porosity and anisotropy can appear in the metallic structure [6]. Porosity can be introduced into AM parts due to incomplete melting of the powder particles or insufficient overlapping of the melt pools [7]. Oscillations in the surface of the melt pool caused by rapid heating and cooling result in powder ejection and splattering of the melt, resulting in surface roughness and porosity [8-10]. Three main types of pores occurring during AM process are gas, keyholes and lack of fusion [11]. Keyhole pores, which are caused by an excess of input energy during the melting process, typically have spheroidal shapes and dimensions on the order of tens to hundreds of microns. Lack of fusion pores, which are caused by a lack of input energy to the powder bed during the melting process, have irregular shapes and dimensions on the order of tens to hundreds of microns. Gas pores, which are related to gas trapped in metal during melting and solidification, have spherical shapes and dimensions on the order of microns. The defects tend to occur in clusters.

Figure 1 – Overview of LPBF: (a) Step 1 prepares the powder bed (b) Fabrication occurs in Step 2 where porosity can be introduced into AM metallic parts due to incomplete melting of powder particles or insufficient overlapping of melt pools [5]

Because reproducibility in AM is currently lower than that of conventional manufacturing, each structure needs to be examined nondestructively before deployment in an environment with high safety requirements, such as inside a nuclear reactor. For AM metallic structures exposed to high temperature and ionizing radiation in a nuclear reactor, material defects could result in lower than expected failure resistance or fatigue life [12-14]. In addition, corrosion damage to AM metallic structures from long term exposure to high-temperature reactor coolant fluids could be accelerated by corrosion front encountering sub-surface pores in the metal [15,16].

Thermography is a potentially promising non-destructive evaluation (NDE) approach to quality control of fabricated AM structures [17-20]. This image-based material characterization method provides a number of potential advantages because measurements are non-contact, one sided, and scalable to arbitrary size structures. Because information is recorded as an image with a megapixel infrared (IR) camera, the amount of mechanical scanning is significantly reduced compared to raster scan imaging with a single probe. Thermographic imaging method used in this project is thermal tomography (TT), which is a computational method for reconstruction and presentation of data obtained from flash thermography measurements [21-23]. Flash thermography utilizes a high intensity flash lamp to rapidly heat surface of sample, and a fast-frame megapixel infrared (IR) camera to capture data of spatial surface temperature distribution $T(x,y)$ [24,25]. The acquired data cube consists of a stack of surface temperature images taken at different times, $T(x,y,t)$. TT algorithm converts $T(x,y,t)$ into spatial 3D thermal effusivity $e(x,y,z)$ [21-23]. Images of effusivity can be used to characterize material flaws. Compared to other NDE systems for imaging of metals, such as X-ray and neutron radiography, thermography hardware offers size/portability and cost advantages.

Alternative approaches to quality control of AM structures could utilize NDE techniques, such as X-ray radiography [26], neutron radiography [27] and ultrasonic waves. Applications of X-ray radiography are limited because of complex shape and lack of symmetry of AM structures. X-ray computed tomography can be used for high-resolution imaging of small coupons shaped in body-of-revolution symmetry form (spheres or cylinders). However, imaging small coupons provides sampled information about the quality of the AM process, but not about the actual printed structure. As the size of the metallic structure increases, higher energy X-rays are required, and imaging resolution typically decreases. Neutron tomography can be used for high-resolution imaging, including detection of pores in AM structures [27]. A source of neutron beam used for material evaluation is typically a nuclear reactor. For evaluation of SS316L with neutron tomography, a potential concern is neutron activation. For example, SS316L is an austenitic chromium-iron-nickel alloy, typically consisting of approximate weight proportions of 65% Fe, 17% Cr, 12% Ni, 3% Mo, 2% Mn. Typical composition of IN718 alloy by weight is given approximately as: Ni 50-55%, Fe 20%, Cr 20%, and minor fractions of several other metals. Neutron activation can potentially create radioactive Fe-59, Cr-51, Ni-65 and Mn-56 high energy (MeV-level) beta and gamma emitters, which have half-lives from hours to months [28]. Handling radioactive materials could be expected to increase complexity and cost of the neutron imaging compared to other NDE approaches. Ultrasonic testing NDE, which involves contact probes, faces challenges because AM

structures have rough surfaces which affect probe coupling. In addition, high-resolution ultrasonic tomography requires time-consuming point-by-point raster scanning of specimens.

In this report, we describe the details of thermal tomography algorithm implementation, and demonstrate its applications to visualization of experimental flash thermography data. Performance of depth reconstruction algorithm is first demonstrated with parametric studies of COMSOL computer simulations of heat transfer in a layered metallic structure. Next, thermal tomography reconstructions are obtained for experimental flash thermography data for a SS316L plate with a variable pattern of flat bottom hole (FBH) indentations. The FBH's have different diameters and depths below the surface, so that the structure has variations in the horizontal x-y plane and along the vertical z-axis. Finally, thermal tomography reconstructions are obtained for an AM IN718 plate containing imprinted hemispherical low density regions, consisting of trapped un-sintered metallic powder. The FBH's have the same size as the imprinted defects in the AM plate, but offer higher imaging contrast. Thermal tomography produces 3D reconstruction of internal defects, with the general trend that defects are more visible when they are closer to the surface.

Thermal tomography performance depends on detection sensitivity, which is limited by experimental noises, such as imaging camera thermal noise, non-uniform illumination of the specimen with the flash lamp. In addition, because detection of flaws is based on heat diffusion, contrast of "hot spots" is reduced due to blurring. In this report, we investigate separation of signal from noise to enhance material flaw detection in thermography images using several machine learning (ML) methods. Performance of the ML methods is evaluated using the data cube obtained from flash thermography imaging of AM specimens. The specimens used in this study are SS-316L and IN718 plates produced with LPBF method, which contain imprinted calibrated porosity defects of various sizes. The ML methods developed and demonstrated in this paper are Spatial-Temporal Blind Source Separation (STBSS) and Spatial-Temporal Sparse Dictionary Learning (STSDL). The STBSS method is developed by combining wavelet-based de-noising with neural learning-based Blind Source Separation (NLBSS) algorithm. The NLBSS method developed recently for ML of thermography images, is based on combining the principal component analysis (PCA) and independent component analysis (ICA), which is implemented as a two-layer neural network. The STSDL method is similarly developed by combining wavelet-based de-noising with the sparse dictionary learning (SDL) method. Performance of the ML methods, as well as the previously developed NLBSS, and established PCA, ICA and SDL methods in detection of flaws in flash thermography data is ranked by F-score and algorithm execution runtime. Results of this paper indicate that STBSS and STSDL outperform existing methods in their capability of defects detection, albeit at the expense of increased runtime.

Finally, we investigate NDE of AM metallic structures with an imaging system based on relatively low-cost and small form factor IR cameras with uncooled microbolometer detectors. In this report, TT reconstructions are obtained for AM SS316L plate with imprinted internal porosity defects of variable sizes. Thermography images obtained with a compact IR cameras have lower quality, as compared to those obtained with high-end cooled semiconductor IR camera, because

of lower sensitivity, lower sampling rate, and strong noises of small IR camera. We demonstrate that reduction in image quality can be partially compensated with machine-learning based image de-noising algorithms. We model IR camera noises using Additive white Gaussian noise (AWGN) model. In principle, AWGN can be removed from images with a Gaussian filter, but this leads to image blurring. We show that quality of images is enhanced using Sparse Coding (SC) and K-means Singular Value Decomposition (K-SVD) ML algorithms, which remove AWGN without blurring the images.

2. Thermal Tomography Imaging

2.1. Mathematical model of depth reconstruction

Thermal tomography is a computational method for heat diffusion-based imaging of solids, which provides 3D visualization of imaging data from flash thermography measurements. Flash thermography utilizes a high intensity flash lamp to rapidly heat surface of sample, and a fast-frame megapixel infrared (IR) camera to capture data of spatial surface temperature distribution $T(x,y)$ [21-23]. The acquired data cube consists of a stack of surface temperature images taken at different times, $T(x,y,t)$. Thermal tomography obtains reconstruction of 3D spatial apparent thermal effusivity $e(x,y,z)$ from the data cube $T(x,y,t)$. Effusivity is a measure of how material exchanges heat with its surroundings, and its 3D reconstruction provides information about AM structure geometry, such as variation in structure thickness, as well as internal material flaws. Reconstructions obtained with thermal tomography have similar features with image reconstructions in optical tomography, despite the fact that the technique and objects are quite different [29]. Thermal tomography has been previously developed to study 3D visualization of ceramic structures, with the application to detection of delamination of ceramic thermal barrier coatings for high temperature turbine blades [30,31]. In this project, we investigate 3D visualization of metallic structures, including internal defects in structures, using thermal tomography. The motivation for this study is development of 3D imaging method for nondestructive evaluation (NDE) of additively manufactured (AM) metallic structures [21-25] and validation of structure shape [32].

The reconstruction model assumes that heat propagation is one-dimensional along the z -coordinate. This assumption is strictly valid for uniform planar structures. However, approximate solutions can be obtained for locally planar structures. Detailed study of non-planar structures is outside the scope of this paper. For 1D heat diffusion,

$$\frac{\partial T}{\partial t} = \alpha \frac{\partial^2 T}{\partial z^2}, \quad (1)$$

where z is the depth coordinate, x and y are coordinates in the transverse plane, and α is thermal diffusivity defined as

$$\alpha = k/\rho c. \quad (2)$$

Here, k is thermal conductivity, ρ is density, and c is specific heat. The reconstructed $e(z)$ at the location (x,y) in the plane is obtained only from the surface temperature transient $T(t)$ measured at the location (x,y) . The algorithm starts with the assumption that the medium can be treated as semi-infinite. The analytic solution for semi-infinite slabs is given as [30,31]

$$T(z,t) = \frac{Q}{\sqrt{\rho c k \pi t}} \exp\left(-\frac{z^2}{4\alpha t}\right), \quad 0 \leq z \leq \infty, \quad (3)$$

where Q is the instantaneously deposited surface thermal energy density (J/m^2). Thermal effusivity, which is a measure of how the material exchanges thermal energy with its surroundings, is defined as

$$e = \sqrt{\rho c k} . \quad (4)$$

Using Equations (3) and (4), one can express observed or apparent time-dependent effusivity of the medium as

$$e(t) = \frac{Q}{T(z=0, t) \sqrt{\pi t}} . \quad (5)$$

One can calculate the maximum of thermal wavefront velocity $\partial T / \partial z$ by setting

$$\frac{\partial^2 T}{\partial z^2} = 0 , \quad (6)$$

which gives characteristic relationship between time and depth

$$z = \sqrt{\pi \alpha t} . \quad (7)$$

Next, spatial and temporal effusivities $e(z)$ and $e(t)$ are related through a convolution integral, where $1/z$ is the transfer function [30,31]

$$e(t) = \int_0^z z^{-1} e(\zeta) d\zeta . \quad (8)$$

Taking z -derivatives of both sides,

$$e(z) = \frac{d}{dz} (ze(t)) = \frac{d}{dz} \left(\frac{zQ}{T(t) \sqrt{\pi t}} \right) . \quad (9)$$

One can simplify Equation (9) by using Equation (7) to obtain

$$e(z) = \frac{d}{dz} \left(\frac{\sqrt{\alpha} Q}{T(t)} \right) . \quad (10)$$

To calculate the z -derivative in Equation (10), one has to relate dz to dt using Equation (7)

$$dz = \frac{\sqrt{\pi \alpha}}{2\sqrt{t}} dt = \frac{\sqrt{\pi \alpha}}{2} \frac{\sqrt{\pi \alpha}}{z} dt = \frac{\pi \alpha}{2z} dt . \quad (11)$$

Therefore, the z -derivative of e can be written as

$$\frac{de}{dz} = \frac{2z}{\pi \alpha} \frac{de}{dt} , \quad (12)$$

so that the final equation for apparent effusivity is

$$e(z) = z \frac{2Q}{\pi\sqrt{\alpha}} \frac{d}{dt} \left(\frac{1}{T(t)} \right) \Bigg|_{t=z^2/\pi\alpha} \quad (13)$$

This shows that spatial reconstruction of apparent effusivity $e(z)$ is given as a product of depth function z and time derivative of the inverse of surface temperature evaluated at time t corresponding to depth z according to Equation (7). Information obtained from thermal tomography is relative because Q is usually not known. In principle, relative information can be converted to absolute scale through calibration. However, for estimation of geometrical parameters and detecting material flaws, relative effusivity reconstruction in non-dimensional units is sufficient.

2.2. Experimental flash thermography imaging system

In the experimental system, data for thermal tomography algorithm is acquired with a flash thermography laboratory system shown in Figure 2 [22]. A schematic depiction of the setup is shown in Figure 2(a), while the photograph of the laboratory system is presented in Figure 2(b). A pulse trigger sends a signal to capacitor to discharge in a circuit containing white light flash lamp. The flash lamp source Balcar ASYM 6400 delivers a pulse of 6400J/2ms thermal energy to material surface. Heat transfer then takes place from the heated surface to the interior of the sample, resulting in a continuous decrease of the surface temperature. For better heat absorption, all materials in this study were spray-painted with washable graphite paint. Blackbody radiation from the material is simultaneously recorded with a fast frame megapixel IR camera. The laboratory setup uses a FLIR X8501sc mid-wave infrared (MWIR) imaging camera, operating in 3-5 μ m band with noise equivalent temperature difference (NETD) of 20mK. X8501sc model provides maximum spatial resolution of 1280x1024, with frame rate at full window of 181Hz. The frame rate can be increased at the expense of reducing the viewing window. The flash lamp is typically positioned at 30cm to 50cm distance to the specimen under investigation. The exact distance and angle of illumination of the flash lamp are determined experimentally for each specimen. This is decided by positioning the IR camera at the focal length of the lens, and placing the flash lamp such that the IR field of view is not blocked, nor does IR camera block the flash. Distribution of incident thermal pulse on the plate is not uniform because the flash light illuminates the metallic plate at an angle. To compensate for this, we have fitted the intensity distribution in the camera frame containing a flash with a polynomial, and then used this polynomial for correction of image intensity in every subsequent frame. In addition, image enhancement and re-scaling algorithms are applied to the data to increase visibility of the features, so that the intensity of reconstructed effusivity images do not directly correspond to material effusivity values.

Figure 2 – Flash thermography experimental setup: (a) Schematic drawing (b) Photograph of actual laboratory system [22].

2.3. Parametric studies of apparent effusivity reconstruction with computer simulations of heat transfer

To obtain estimates of thermal tomography sensitivity to defects in LPBF, we reconstruct apparent effusivity from data generated with COMSOL computer simulations of heat transfer in a layered metallic structure. The structure modeled in COMSOL is a stainless steel disc with $R=30\text{cm}$ radius and $L=5\text{mm}$ thickness. Diffusion of heat in a plate with such geometry (transverse dimensions are much larger than the thickness) closely resembles the case of an infinite plate of finite thickness. For the solid media in the structure, we used stainless steel 316L thermophysical parameters $\rho=7954\text{ kg/m}^3$, $k=13.96\text{ W/m}\cdot\text{K}$, $c = 499.07\text{ J/kg}$ [33]. For modeling the amplitude of defect layer, we linearly scaled the thermophysical parameters as $\eta\rho$, ηc and ηk , where ρ , c and k are those of the solid metal, and the scaling parameter values are in the range $\eta=0.7$ to 0.9 . The range of scaling parameter values was chosen to correspond to that of the filling factor of unsintered metallic powder. According to random close packing (RCP) model, packing density of mono-dispersed spheres is 0.65 [34], but size distribution and non-spherical shapes of powders may result in higher packing density [35]. Working in normalized units, we set $\rho=c=k=1$ for solid medium, so that $e_{\text{solid}} = 1$. While density and heat capacity typically scale linearly with powder filling factor, scaling of thermal conductivity is potentially nonlinear. Therefore, this study provides information about parametric dependence of effusivity reconstruction, where a hypothetical defect does not exactly correspond to a physical powder model.

The defect was introduced into the structure as a layer of metallic material with lower thermophysical parameters than those of the host solid plate. In LPBF, heat diffusion is likely to result in smooth transitions from solid metal to defect. The defect was introduced into COMSOL grid as a subtracted Gaussian with the mean of μ and standard deviation σ . Thus, in normalized units, the defect actual effusivity is modeled as

$$e_{\text{actual}}(z) = \left(1 - (1 - \eta)e^{-(z-\mu)^2/2\sigma^2}\right)^{3/2} \quad (14)$$

Defects with equivalent width of $d=500\mu\text{m}$ and $d=50\mu\text{m}$ were considered in COMSOL computer simulations of the layered model. The defects were modeled as subtracted Gaussians with $\mu = 1.25\text{mm}$ and $\sigma = 50\mu\text{m}$, and $\mu = 1.025\text{mm}$ and $\sigma = 5\mu\text{m}$, respectively. Actual effusivities for the two defects are plotted in Figures 3(a) and 3(b) [36]. The scaling parameter η in both figures is in the range from 0.7 to 0.9.

Figure 3 – Actual effusivities in normalized units for $L=5\text{mm}$ plate with a defect layer with equivalent thickness of (a) $d=500\mu\text{m}$ and (b) $d = 50\mu\text{m}$ [36].

In COMSOL computer simulations, the plate is initially at room temperature, and the incident heat source is a Gaussian pulse with variance of 0.5ms. Although the reconstruction model in thermal tomography assumes that heat was deposited instantaneously on the material surface, real flash heat sources have a finite duration time. High intensity flash is usually generated by discharging a capacitor through a white light lamp, with typical capacitor time constant on the order of a few milliseconds (see Figure 2). Thermal insulating boundary conditions were selected for all plate surfaces. Temperature transients were calculated with 0.1ms time step for 20s total problem runtime. Temperature data was exported from COMSOL to perform apparent effusivity reconstruction with algorithm implemented in MATLAB. We observed in COMSOL simulations that the surface temperature of the plate is maximum at the time when the incident Gaussian heat pulse reaches the maximum value. While heat is still applied by the pulse, surface plate temperature begins to decay due to diffusion of heat into the bulk of the plate. This affects the decay rate of the surface temperature. Therefore, when performing effusivity reconstruction, the origin of the surface temperature transient should be chosen such that the heat source has no effect on surface temperature decay. The starting time for the temperature transient used for effusivity reconstruction is 8ms after the surface temperature reaches the maximum value.

Figures 4(a), 4(b) and 4(c) show apparent effusivity reconstructions for scaling parameter $\eta = 0.7, 0.8$ and 0.9 , respectively [36]. In each figure, reconstructions are shown for a structure containing a defect with $d=500\mu\text{m}$ layer and another structure containing $d = 50\mu\text{m}$ layer. Apparent

effusivity reconstruction $e(z)$ is plotted as a normalized variable. In the sketch of the layered structure shown in Figure 4, the front and back planes are at $z=0$ and at $z=5$, respectively. Detection of defect is interpreted as deviation from the effusivity reconstruction for a defect-free solid plate. The defect layer is indicated as 500 μm and 50 μm -thick stripes overlaid on the solid plate structure colored in grey. The strip is slightly larger than 2σ width of the Gaussian model of the defect. One can observe from Figure 4 that the reconstruction for a solid plate with no defect (yellow curve) agrees well at the front edge of the plate. However, reconstruction is blurred at the back edge of the plate. As the scaling factor η is decreased, apparent effusivity depth profile curve shows a dip in the spatial region corresponding to the defect. As expected, the dip decreases with increasing value of η .

Figure 4 – Apparent effusivity $e(z)$ reconstructions for variable defect thermophysical properties from surface temperature transients produced with COMSOL computer simulations data of heat transfer [36]. The structure has $L=5\text{mm}$ total thickness with Gaussian defect. Thermophysical parameters of the defect layer are scaled as $\eta\rho$, ηc and ηk , where ρ , c and k are those of the SS316L solid metal, and the scaling parameter values are in the range (a) $\eta=0.7$ (b) $\eta=0.8$ (c) $\eta=0.9$.

Quantitative analysis of the data in Figure 4 is shown in Table 1. Reconstructed effusivity of the defect is obtained by measuring the minimum value at the dip of the effusivity curve. Based

on computer simulations for defects located below 1mm depth, reconstruction of the defect with 500 μ m thickness offers approximately 10% to 5% contrast, while reconstruction of the defect with 50 μ m thickness offers approximately 5% to 2% contrast relative to solid plate effusivity.

Table 1 – Apparent effusivity of defect layer obtained from COMSOL computer simulations.

η	Defect apparent effusivity (normalized units)	
	500 μ m	50 μ m
0.7	0.89	0.95
0.8	0.93	0.96
0.9	0.96	0.98

Our results based on computer simulations of heat transfer in a layered media indicate that detection of defects as small as 50 μ m located at 1mm depth in SS316L can be possible, in principle. Because results are obtained from simulated data with no experimental noise, results based on computer simulations are likely to give the upper bound for detection of material defects with thermal tomography reconstructions of experimental data. In addition, sensitivity threshold of IR camera in detecting temperature differences has to be taken into consideration. Future work will be aimed performing experimental validations of thermal tomography sensitivity with imprinted calibrated defects.

2.4. Thermal tomography imaging of internal defects

To investigate performance of thermal tomography, reconstructions are obtained for two types of calibrated defects of similar dimensions. First, thermal tomography reconstructions are obtained from experimental flash thermography data for a SS316L plate with a variable pattern of flat bottom hole (FBH) indentations. The FBH's have different diameters and depths below the surface, so that the structure has variations in the horizontal x-y plane and along the vertical z-axis. Next, thermal tomography reconstructions are obtained for an AM IN718 plate containing imprinted hemispherical low density regions, consisting of trapped un-sintered metallic powder. The FBH's have the same size as the imprinted defects in the AM plate, but offer higher imaging contrast.

2.4.1. Imaging of flat bottom holes calibrated defects in a metallic plate

We have investigated thermal tomography detection and imaging of calibrated defects consisting of a pattern of drilled cylindrical flat bottom holes (FBH) indentations of varying size and depth below the flat surface of SS316L plate. The structure has variations in the horizontal x-y plane, and along the vertical z-axis. SS316L is an austenitic chromium-iron-nickel alloy, typically consisting of approximate weight proportions of 65% Fe, 17% Cr, 12% Ni, 3% Mo, 2%Mn, and small fractions of Si and C. FBH indentation is a common surrogate model of delamination [30,31]. Because FBH defects are expected to result in better contrast in thermal tomography images, imaging of FBH defects was performed as a calibration study for subsequent imaging of imprinted defects of the same size in the AM plate. Computer rendering of the specimens and the drawing

of defects (all dimensions are in mm) are shown in Figure 5 [22]. Computer rendering of the plate with FBH indentations is shown in Figure 5(a). Dimensions of the FBH plate are $76.2\text{mm} \times 76.2\text{mm} \times 6\text{mm}$. Figure 5(b) provides a drawing with labels showing diameters of the defects and their depths relative to surface. All dimensions are in mm. The notation is ϕ = diameter and d = depth. For example, $(\phi 1, d 2)$ indicates that the defect has diameter of 1mm, and located at depth 2mm below the surface. Depth is measured as the distance from the top of FBH indentation to the flat surface for FBH plate. The defects have diameters 1, 2, 3, and 4mm and depths 1, 2, 3, 4, and 5mm. Because of SS316L material high strength, the smallest FBH defect we could create with drilling had 1mm diameter. As shown in Figure 5(b), the diameters of defects decrease along the vertical dashed lines, while the depth of these defects along these lines is constant. Along the horizontal dashed lines, depth of defects increases, while the diameter is fixed.

Figure 5 – (a) Visualization of SS316L plate with flat bottom hole (FBH) indentations. (b) Layout of defects diameters ϕ and depths d below the surface (all dimensions are in mm) [22].

The FBH plate depicted in Figure 5 was imaged with flash thermography with the flat surface of the plate oriented towards the IR camera. Total imaging time was approximately 8s. Imaging resolution is $230\mu\text{m}/\text{pixel}$. We used the literature value of $\alpha=3.529\text{mm}^2/\text{s}$ for SS316L for estimation of reconstruction depth [20]. Note that thermal tomography reconstructions of the FBH plate is equivalent to reconstruction of a stack of plates with variable width and thickness.

Figure 6 shows apparent effusivity reconstructions of the FBH plate in the parallel and vertical planes [22]. Reconstructions in the parallel plane at estimated depths of $z = 1\text{mm}$ and $z = 2\text{mm}$ are shown in Figures 6(a) and 6(b), respectively. The depths of reconstruction are selected to match the depths of FBH's, as shown on Figure 5(b). As the depth of reconstruction in Figure 6 increases, it is expected to observe the column of FBH's at the corresponding depth, as well FBH's from all the columns of smaller depths. In the reconstruction at $z = 1\text{mm}$ in Figure 6(a), all FBH's of the right-most column of Figure 5(b) with $d = 1\text{mm}$ and $\phi = 4, 3, 2,$ and 1mm are visible. In the reconstruction at $z = 2\text{mm}$ in Figure 6(b), FBH's of the second column from the right of Figure 6(b) with $d = 2\text{mm}$ and $\phi = 4, 3,$ and 2mm are clearly visible. In addition, all FBH's from $d = 1\text{mm}$ depth can be observed in Figure 6(b).

Vertical plane thermal tomography reconstructions of the FBH's in columns at $d = 1\text{mm}$ and $d = 2\text{mm}$ depths are shown in Figures 6(c) and 6(d), respectively. The diameters of the FBH's in

Figures 6(c) and 6(d) are $\phi = 1, 2, 3$, and 4 mm, increasing from left to right. Actual outline of the FBH's in the plate is indicated with solid black lines in Figures 6(c) and 6(d). All FBH's are visible in Figures 6(c), while three larger ones are visible in Figures 6(d). This is consistent with visibility of defects in Figures 6(a) and 6(b). The general trend in these reconstructions in Figures 6 is that smaller defects are visible when they are at shallow depth. Because of increasing blurring in reconstruction with depth, which is a common issue in tomography based on diffusing waves, the shapes of reconstructed FBH's appear as truncated cones. Comparing between Figures 6(c) and 6(d), location of the same-diameter FBH top is observed to be progressively lower relative to top of the plate, which is expected. Depth of the FBH's in Figures 6(c) and 6(d) are estimated to be approximately at 1.15mm depth with 15% error, and at 2.53mm with 26.5% error, respectively. Overall thickness of the plate is estimated to be 6.9mm with 15% error. Higher relative effusivity spots can be seen appearing at the bottom of FBH in Figure 6(c). These can be potentially attributed to heat diffusion over the surface of the FBH, which is slower than diffusion of heat in neighboring regions of the solid plate. In general, it is possible to observe an increase in apparent effusivity in deeper layers of a structure containing an FBH. Since effusivity is proportional to temperature decay rate, the top of an FBH has relatively lower effusivity because temperature is decaying faster in the uniform areas of the plate around the FBH. However, at some point, heat is reaching the bottom of the plate, and temperature decay rate in uniform areas of the plate decreases. At the same time, heat is diffusing around the cylindrical surface of the FBH with higher temperature decay rate, as compared to the surrounding uniform regions of the plate.

Figure 6 – Thermal tomography reconstruction of apparent effusivity for SS316L FBH plate [22]. Imaging resolution is $230\mu\text{m}/\text{pixel}$. (a) Horizontal plane reconstruction at $z = 1\text{mm}$ depth. (b) Horizontal plane reconstruction at $z = 2\text{mm}$ depth. (c) Vertical plane reconstruction of FBH's located along the column for $d = 1\text{mm}$. (d) Vertical plane reconstruction of FBH's located along the line $d = 2\text{mm}$.

2.4.2. Imaging of imprinted internal defects in AM metallic plate

In the next experiment, IN718 plate was fabricated with LPBF method, in which internal defects were imprinted in the form of hemispherical porosity regions containing un-sintered powder. Typical composition of alloy by weight is given approximately as: Ni 50-55%, Fe 20%, Cr 20%, and minor fractions of Nb, Mo, Ti, Al, C, S and Cu. The plate was fabricated using direct metal laser melting (DMLM) method, which is one of the variants of the LPBF category of AM methods. Fabrication was based on $40\mu\text{m}$ powder layers. The defects were imprinted into the plate during fabrication using an STL (sterelithography) file with a drawing of the pattern of defects. Dimensions of the AM plate are $76.2\text{mm} \times 76.2\text{mm} \times 10\text{mm}$, same as FBH plate shown in Figure 6. Visualization of the AM IN718 plate with internal defects is shown in Figure 7(a) [22]. The pattern of defects, with the same diameters and depths relative to flat surface, is shown in Figure 7(b) [22].

Figure 7 – (a) Visualization of imprinted hemispherical defects in IN718 plate [22]. (b) Layout of defects diameters ϕ and depths d below the surface (all dimensions are in mm).

The IN718 metallic plate depicted in Figure 7 was imaged from the top surface, i.e., with the hemispherical spherical side of the internal defects oriented towards the IR camera. Imaging resolution was $130\mu\text{m}/\text{pixel}$. Total imaging time was approximately 10s. We used the literature value of $\alpha=3.019\text{mm}^2/\text{s}$ for IN718 at room temperature for estimation of reconstruction depth in the AM plate. Figure 8 shows apparent reconstructed effusivity of the structure in horizontal and

vertical planes [22]. Figures 8(a) and 8(b) display effusivity reconstructions in horizontal plane at estimated depths of $z = 1\text{mm}$ and $z = 2\text{mm}$, respectively. Similar to the case of the FBH plate, these reconstructions are selected to match the depth of the imprinted hemispherical defects. In the reconstruction at $z = 1\text{mm}$ in Figure 8(a), all four imprinted defects at $d = 1\text{mm}$ with $\phi = 4, 3, 2$, and 1mm are visible. This result is similar to that for FBH plate in Figure 6(a). In the reconstruction at $z = 2\text{mm}$ in Fig. 7(b), defects at $d = 2\text{mm}$ with $\phi = 4, 3$, and 2mm and at $d = 1\text{mm}$ with $\phi = 4, 3$, and 2mm are visible. Compared to same depth reconstruction for the FBH plate in Fig. 6(b), the defect at $d = 1\text{mm}$ and $\phi = 1\text{mm}$ is not visible in Fig. 9(b).

Figures 8(c) and 8(d) show thermal tomography reconstructions of apparent effusivity in the vertical plane along the lines drawn through the column of defects located at $d = 1\text{mm}$ and $d = 2\text{mm}$ depths, respectively. Actual locations of imprinted defects are indicated in Figures 8(c) and 8(d) with hemispherical contours. Diameters of defects in Figures 8(c) and 8(d) are increasing from left to right. Defects with $\phi = 2, 3$, and 4mm are visible in Figures 8(c). Although the smallest defect with $\phi = 1\text{mm}$ was observed in the horizontal plane reconstruction in Figure 8(a), the contrast of this defect is weaker compared to larger-diameter ones. Faint signs of defect with $\phi = 4\text{mm}$ can be seen with low contrast in the image in Figure 8(d). From the images, the defects in Figures 8(c) and 8(d) are estimated to be approximately at depth of 1.17mm with 17% error and depth of 2.47mm with 23.5% error in reconstruction, respectively. Overall thickness of the plate is estimated to be 10.4mm with 4% error. The defects in the images of Figures 8(c) and 8(d) appear to have hemispherical shapes. Compared to vertical plane reconstructions of FBH's in Figure 6, the images of vertical plane reconstructions of imprinted defects in AM plate in Figure 8 have lower contrast. This is expected since thermal diffusivity density gradient near defects is higher for FBH's. Unlike the case of FBH plates, no effusivity hot spots are observed below the reconstruction of defects.

Figure 8 – Apparent effusivity reconstructions for AM IN718 plate containing imprinted hemispherical regions of porosity [22]. Imaging resolution is $130\mu\text{m}/\text{pixel}$. (a) Horizontal plane reconstruction at $z = 1\text{mm}$ depth. (b) Horizontal plane reconstruction at $z = 2\text{mm}$ depth. (c) Vertical plane reconstruction along the column of defects at $d = 1\text{mm}$ (b) Vertical plane reconstruction along the column of defects at $d = 2\text{mm}$.

In general, internal defects with smaller diameter and deeper location are more difficult to detect. The reason is that defects of smaller size have smaller thermal resistance, and hence less visible on the plate surface because heat can diffuse around these defects. In addition, thermal resistance of defects located deeper below the surface manifests itself when surface temperature has decayed to the level close to the ambient temperature. These factors result in low thermal contrast “hot spots” on the specimen surface, which are difficult to detect when the contrast approaches noise equivalent temperature difference (NETD) threshold of the IR camera. Further improvements in flash thermography hardware, such as increasing flash power, and using a microscopic lens to increase the number of pixels per an image of a defect could enhance detection resolution. In addition, signal processing, such as image de-noising algorithms can potentially improve the quality of reconstructions.

3. Machine Learning Algorithms for Thermography Image Analysis

Efficiency of thermal tomography depends on the ability to detect material flaws in thermographic images. Raw images obtained from flash thermography typically suffer from low visibility contrast of subtle features with low signal to noise ratio (SNR). This typically occurs in flash thermography images because of thermal noises, non-uniform illumination of specimen with flashlight, insufficient noise equivalent temperature difference (NETD) sensitivity threshold of the IR camera, and blurring of features due to diffusion-based imaging. In this paper, we investigate extraction of low SNR features corresponding to material defects in thermal images using unsupervised ML algorithms, including new STBSS and STSDL methods. Unsupervised ML aims to learn potential patterns in unlabeled datasets, with minimal human supervision [37]. Common algorithms used in unsupervised learning are clustering analysis [38] and latent variable models learning [39]. Clustering analysis, such as hierarchical clustering, k-means clustering, is used to group datasets with the same attributes into one cluster. For latent variable models learning, including the PCA [40], expectation maximization (EM) algorithm and blind source separation (BSS) [41], the approach is to learn latent features that are not directly observed but inferred from observed datasets. The objective of PCA is to extract principal features of datasets by reconstructing new basis vectors to reduce information redundancy, which follows the same learning pattern as the unsupervised representation learning [42]. The unsupervised representation learning, such as SDL and ICA aim to identify the underlying explanatory features hidden in observed data. BSS aims to separate each latent source signal which shares the same attributes from mixed signals, and combines the representation learning with clustering analysis to enhance the performance.

3.1. Spatial-Temporal Blind Source Separation (STBSS) Algorithm

The STBSS approach is based on a neural learning based blind source separation (NLBSS) [25]. The improvement of this method described below is achieved by introducing spatial de-noising with wavelet transform [43]. NLBSS algorithm, which combines PCA and fast ICA to enhance defect detection in time and space by separating defects from background and identifying the presence of defects [44]. PCA is a commonly used ML method for dimensionality reduction and feature extraction, which is applied for thermography defects detection as principal component thermography (PCT) [45]. ICA is another frequently used method for separating a multivariate signal into additive subcomponents. Figure 9 shows the flow chart of STBSS algorithm, the schematics of which are discussed in the sub-sections below [23].

Figure 9 – Flowchart of the STBSS algorithm [23].

3.1.1. Wavelet Transform spatial de-noising

Wavelet transform is used to reduce the high-frequency thermography image noises in spatial-domain. These noises are random variation of brightness or color information in images and normally include the Additive White Gaussian Noises (AWGN), which can be efficiently reduced by using the wavelet transformation [46]. Wavelet transforms are mathematical methods to perform signal analysis when signal frequency changes over time. For image signals, the wavelet analysis selects the appropriate frequency band adaptively, then analyzes and filters abrupt changes in images, such as AWGN, to improve the image resolution.

As shown in Figure 9, wavelet transformation is applied to de-noise image noises for each observed thermography images X to obtain data cube X' . The flash thermography data cube can be written as $X \in R^{m \times n \times l}$, where l is the number of images (time frames), and each image has $m \times n$ pixels. Each image of the 3D data cube X is decomposed using wavelet transformation into four images with size $m \times n$, which includes one reconstruction image and three high-pass wavelet images. We keep the reconstruction images to form a new thermography data cube $X' \in R^{m \times n \times l}$, and discard the high-pass wavelet images which contain most image noise. In this study we apply the two-level Biorthogonal wavelet transformation implemented with the 'bior3.5' wavelet filter, which has advantages of filtering image noises with minimal impact on image contrast gradients.

In the numerical experiments, the filter was implemented using MATLAB library of wavelet filters.

3.1.2. Neural Learning-based Blind Source Separation (NLBSS) algorithm

In NLBSS, we use PCA [47] to extract principal features of thermography data, thus reducing thermal imaging noises and artifacts. As shown in Figure 9, PCA is used to pre-process images X' to obtain principal components U . Next, U become inputs to the neural learning-based ICA [25] to estimate independent source signals $\hat{S}$, which are the thermal sources images (TSI) of defects. the ICA [48], implemented in a two-layer neural network structure, is applied to automatically separate image regions containing signatures of material defects from image regions which do not contain any material flaws. W is the estimation matrix for separating the mixed thermograms into TSIs of defects. The ICA is implemented in a neural network structure, which is composed of densely connected input layer (thermograms U), and an output layer (estimated source signal $\hat{S}$). The input layer has 50 neurons, equal to the number of principal components. The output layer has 12 neurons, equal to the number of independent components. Nonlinearity function 'pow3' ($g(u) = u^3$) [49] is used as the activation function to optimize training for robust convergence. Next, we use the reverse entropy [46] as the objective function to measure the non-Gaussian. We train this two-layer neural network with 100 epochs to estimate the TSI of defects. The neural network structure utilizes the fast fixed-point algorithm [49] for optimization to speed up detection of features in thermography images.

3.2. Spatial-Temporal Sparse Dictionary Learning (STSDL) Algorithm

The STSDL approach is based on sparse dictionary learning (SDL) method. SDL is a representation learning method which aims to find the sparse representation of the data. The new method STSDL consists of three stages of feature extraction to enhance defects detection for weak defect signals: wavelet transform, singular value decomposition (SVD), and SDL. Figure 10 shows the flow chart of the STSDL algorithm, the schematics of which are discussed in sub-sections below [23].

Figure 10 – Flowchart of the STSDL algorithm [23].

3.2.1. Wavelet Transform spatial de-noising

As shown in Figure 10, in the 1st stage of feature extraction, we apply the two-level Biorthogonal wavelet transformation implemented with the 'bior3.5' wavelet filter, which has advantages of filtering image noises with minimal impact on image contrast gradients. The details of wavelet transform implementation are the same as described in Section 3.1.1. The output of the wavelet filter is de-noised thermography data cube $X' \in R^{m \times n \times l}$, where there are l images, each having $m \times n$ pixels.

3.2.2. Singular Value Decomposition

We use the Singular Value Decomposition (SVD) to extract principal features of defect information for the 2nd stage feature extraction, as shown in Figure 10. Defects features are compressed in time-domain by reconstructing orthogonal thermography features to ameliorate thermal imaging experimental artifacts, such as uneven heating and image noises. The equation implementing SVD is

$$Y_{M \times N} = U_{M \times N} H_{N \times N} V_{N \times N}^T. \quad (15)$$

To apply Equation (15) to 3D thermography data cube $X' \in R^{m \times n \times l}$ obtained with Biorthogonal wavelet transformation described in Section 3.2.1, we reshape the array of $m \times n$ pixels in each

image into a single vector of length $M=m \cdot n$. The condensed 2D data is stored in matrix Y , where M and N represent the number of rows and columns, respectively ($N=l$ is the renamed number of recorded thermography frames). U and V are orthogonal matrices separately containing variability of data and time information. H is the matrix containing the singular values of Y . Thus, by decomposing the thermography data Y with SVD, the matrix U is constructed with orthogonal basis vectors which describe the largest variability in the data using the first few columns (N_l) of U . We use only few basis vectors of U , which contain principal features of data, as input for SDL to enhance detection of flaws.

3.2.3. Sparse Dictionary Learning (SDL)

SDL method aims to find the sparse representation of data by searching for the optimized basis vectors of dictionary. The dictionary includes the optimized basis vectors called atoms, which are linearly combined to represent defect information. Compared to BSS method, SDL allows more flexibility in sparse representation of defects information the atoms are not required to be orthogonal. In this study, we use the SDL to optimize the representation of data and further enhance extraction of features in thermography images corresponding to material defects. The objective function of the SDL algorithm is modeled as

$$\underset{R,D}{\text{minimize}} \|U - (RD')\|_1 + \frac{\gamma_r}{2} \|R\|_2^2 + \frac{\gamma_d}{2} \|D\|_2^2. \quad (16)$$

In Equation (16), U is the matrix consisting of the 2D data matrix obtained with SVD. The matrices D and R are the dictionary matrix and representation matrix, respectively. Thus, the first term in Equation (16) that measures the difference between U and (RD') models the reconstruction error, which is minimized to reduce information loss by forcing the algorithm to yield an optimal representation of the thermography data. Here the difference is measured with L_1 norm (linear norm) which gives more robust convergence compared with L_2 norm (squared norm). The second term imposed the constraint of sparse representation. Here γ_r is a scaling constant that determines the tradeoff between the reconstruction error and representation sparsity. The third term constrains atoms in dictionary from reaching arbitrarily high values resulting in low values of R . In the third term in Equation (16), γ_d is a scaling penalty constant. The second and third terms are regularized by L_2 norm to ensure sparsity and convergence for optimization.

Direct solution of the minimization problem in Equation (16) is computationally expensive since the Laplace distribution is not smooth. To circumvent this issue, a two-level hierarchical form of the Laplacian distribution is used [50]. The conditional expectation maximization (CEM) algorithm is utilized to iteratively search for D , R , while de-correlating the dependency between D and R . Therefore, in each CEM iteration there are two expectation maximization (EM) steps, which consist of updating D while keeping R fixed, and updating R while keeping D fixed. Matrix $T = [t_{ij}] \in R^{m \times n}$ is introduced as exponential prior for each pre-processed element u_{ij} to represent the missed data, and $\delta = [R, D]$ represents the parameters to be estimated. The constants γ_d and

γ_r are hyperparameters for fine-tuning optimization. Then, in one EM step, we apply the Q function to estimate the dictionary matrix D while keeping the representation matrix R known:

$$Q(D|\hat{\delta}) = E_T[\log p(D|\hat{R}, U, T) | U, \hat{\delta}]. \quad (17)$$

The Q function computes the expectation of the complete-data log-posterior regarding the missed data T , given the current estimates of parameters $\hat{\delta} = [\hat{R}, \hat{D}]$ in Equation (17).

To solve Equation (17), we apply the Bayes's rule, take log on both sides and remove terms which are irrelevant to parameter D . Then the complete-data log-posterior $\log p(D|U, T)$ is represented as

$$\log p(U|D, \hat{R}, T) + \log p(D) = -\frac{1}{2} \sum_i^m \sum_j^n [t_{ij}^{-1} (u_{ij} - \hat{r}_i' d_j)^2] - \frac{\gamma_d}{2} \sum_j^n d_j' d_j + C. \quad (18)$$

In Equation (18), C is a constant which does not depend on D and R . The posterior expectation of t_{ij}^{-1} is computed for the (expectation) E-step based on the observation that t_{ij}^{-1} follows the inverse Gaussian distribution. Then in the (maximization) M-step, we update the parameter estimate d_j in each row of D by maximizing the Q function shown in Equation (17). Next the partial derivative of the Q function with respect to d_j is set to zero, and we obtain closed-form update equation

$$d_j = (\hat{R}' \Omega_j \hat{R} + \gamma_d I_\theta)^{-1} \hat{R}' \Omega_j u_{\cdot j}. \quad (19)$$

In equation (19), $\Omega_j = \text{diag} \{ (t_{1j}^{-1}), \dots, (t_{mj}^{-1}) \}$, $\theta_{ij} = u_{ij} - (rd')_{ij}$, and $u_{\cdot j}$ is the j^{th} column of U . In the next EM step, we update matrix R while keeping matrix D fixed by following the same procedure described above. The closed-form update equation is

$$r_i = (\hat{D}' \Lambda_i \hat{D} + \gamma_r I_\theta)^{-1} \hat{D}' \Lambda_i u_{i\cdot}. \quad (20)$$

In equation (20), $\Lambda_i = \text{diag} \{ (t_{i1}^{-1}), \dots, (t_{in}^{-1}) \}$ and $u_{i\cdot}$ is the i^{th} row of U . Then, the convergence criteria is set as

$$\frac{\| (RD')^i - (RD')^{i-1} \|_2}{\| U \|_2} \leq \varepsilon. \quad (21)$$

Here L_2 normalization is used for calculating the convergence criteria, where ε is the threshold set to be $\varepsilon = 5 \times 10^{-3}$. If the convergence criterion is satisfied, which means that the difference between old and new values from SDL reconstruction is small, then parameters R and D are used to further extract features from thermography data to enhance defects detection. Otherwise, we apply the CEM algorithm for the next iteration to update parameters R and D .

3.3. Development of additively manufactured metallic specimens

A set of two SS-316L and one INC718 plates was fabricated with LPBF method using EOS metal 3D printer. Fabrication of SS-316L and INC718 plates was based on 20 μ m and 40 μ m powder layers, respectively. The dimensions of the plates are Length $\times$ Width $\times$ Thickness: 152mm $\times$ 76mm $\times$ 10mm. The same pattern of calibrated defects consisting of hemispherical porosity regions containing un-sintered metallic powder were imprinted into the SS-316L and INC718 plates. The defects were imprinted during fabrication using an STL (sterelithography) file with a drawing of the pattern of hemispherical inclusions. In one of the SS-316L plate (SSH316) and the INC718 plate, defects consisted of 100% porosity (high porosity). In another SS-316L plate (SSL316) speed and power of the laser were adjusted to yield approximately 40% porosity in the defect regions (low porosity).

A computer rendering of the pattern of defects is shown in Figure 11 (top panel) [23]. A drawing with labels showing diameters and depths of the imprinted defects is provided in Figure 11 (bottom panel). Note that there are two patterns of defects on the plate: one with diameters $\phi = 5, 6$ and 8mm and depths $d = 2, 3, 4$, and 5mm, and another one with diameters $\phi = 1, 2, 3$, and 4mm and depths $d = 1, 2, 3, 4$ and 5mm. The diameters of defects decrease along the lines parallel to the longer side of the plate, while the depth along these lines is held constant. Along the lines parallel to the shorter side of the plate, the depth increases, while the diameter is fixed along these lines.

Figure 11 – (Top) 3D rendering of hemispherical porosity defects imprinted in AM specimens. (Bottom) Design pattern of hemispherical defects of different diameters and depths relative to plate surface (all dimensions are in mm) [23].

Figure 12 shows the photograph of two SS-316L and one INC718 plates used in this study [23]. The plates are visibly smooth on both sides.

Figure 12 – Photograph of two SS-316L and one INC718 plates manufactured with LPBF method [23].

3.4. Benchmarking of machine learning algorithms performance

Performance of ML algorithms in extracting features corresponding material flaws in images was evaluated using flash thermography data. Visualization of ML performance results in flaw detection in images (total of 36 images) is presented in Figure 13 [23]. Data was obtained from measurements performed on SSH316 (high porosity defects), SSL316 (low porosity defects), and INC718 specimens. Separate thermography measurements were performed for large defects (see Figure 13(a)) and small defects patterns (see Figure 13(b)) in all plates, for a total of six measurements. In both Figures 13(a) and 13(b), there are six rows, with the labels indicating the types of ML algorithms used in the analysis. There are three columns in each figure, with labels indicating the types of AM specimen used in the corresponding flash thermography measurement. For baseline comparison, we include commonly used ICA, PCT, and recently developed NLBSS. Performance of STBSS algorithm, described in Section 3.1, is compared to the preceding three methods. Next, for baseline comparison, performance of SDL algorithm is shown. This is followed by demonstration of results obtained with the new STSDL algorithm described in Section 3.2.

Figure 13 – Visualization of ICA, PCA, BSS, STBSS, SDL and STSDL algorithms performance in detection of in SSH16 (high porosity), SSL316L (low porosity), and INC718 specimens [23].
 (a) Pattern of large imprinted defects. (b) Pattern of small imprinted defects

Results of benchmarking ML algorithms performance using F-score and execution runtime are shown in Figure 14 [23]. The F-score, which is a measure of test accuracy, indicates how well the ML algorithms separate true signal from noise. There were 12 imprinted “larger” defects and 20 imprinted “smaller” defects. The F-score is proportional to how many defects from the total set of imprinted defects were detected. The values of the F-score are between 0 and 1, with the higher number indicating better accuracy. The F-scores in Figure 14 were calculated as

$$F_{score} = \frac{(\beta + 1) \times (Precision \times Recall)}{\beta^2 \times (Precision + Recall)}, \quad (22)$$

$$Precision = T_p / (T_p + F_p) \text{ and } Recall = T_p / (T_p + F_n). \quad (23)$$

Here T_p = true positive, F_p = false positive, F_n = false negative, β is the tradeoff (relative) parameter which determines if *Precision* or *Recall* is more important. In this study $\beta = 1$, which means *Precision* and *Recall* are equally important.

	ICA		PCT		NLBSS		STBSS		SDL		STSDL	
	Detected defects Diameter,depth (ϕ , d) mm		Detected defects Diameter,depth (ϕ , d) mm		Detected defects Diameter,depth (ϕ , d) mm		Detected defects Diameter,depth (ϕ , d) mm		Detected defects Diameter,depth (ϕ , d) mm		Detected defects Diameter,depth (ϕ , d) mm	
	F-score	Time	F-score	Time	F-score	Time	F-score	Time	F-score	Time	F-score	Time
Larger defects SSH316 12 Defects	($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 6$, $d 2$), ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 8$, $d 4$), ($\phi 6$, $d 2$) ($\phi 6$, $d 3$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 8$, $d 4$), ($\phi 8$, $d 5$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 5$, $d 2$), ($\phi 5$, $d 3$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 8$, $d 4$), ($\phi 8$, $d 5$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 6$, $d 4$), ($\phi 5$, $d 2$) ($\phi 5$, $d 3$), ($\phi 5$, $d 4$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 8$, $d 4$), ($\phi 8$, $d 5$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 6$, $d 4$), ($\phi 5$, $d 2$) ($\phi 5$, $d 3$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 8$, $d 4$), ($\phi 8$, $d 5$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 6$, $d 4$), ($\phi 5$, $d 2$) ($\phi 5$, $d 3$), ($\phi 5$, $d 4$)	
	0.5	52	0.59	7	0.8	10	0.91	112	0.86	14	0.96	130
Larger defects SSL316 12 Defects	($\phi 8$, $d 2$), ($\phi 6$, $d 2$)		($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$), ($\phi 8$, $d 3$) ($\phi 6$, $d 3$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 8$, $d 4$), ($\phi 6$, $d 2$) ($\phi 6$, $d 3$), ($\phi 6$, $d 4$) ($\phi 5$, $d 2$), ($\phi 5$, $d 3$) ($\phi 5$, $d 4$)		($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 5$, $d 2$), ($\phi 5$, $d 3$)	
	0.29	100	0.4	7	0.59	12	0.86	133	0.4	14	0.67	74
Larger defects INC718 12 Defects	($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 5$, $d 2$), ($\phi 5$, $d 3$)		($\phi 8$, $d 2$), ($\phi 6$, $d 2$) ($\phi 5$, $d 2$)		($\phi 8$, $d 2$), ($\phi 8$, $d 3$) ($\phi 6$, $d 2$), ($\phi 6$, $d 3$) ($\phi 5$, $d 2$), ($\phi 5$, $d 3$)	
	0.4	57	0.4	8	0.4	10	0.67	86	0.4	22	0.67	75
Smaller defects SSH316 20 Defects	($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$) ($\phi 4$, $d 3$), ($\phi 1$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$) ($\phi 4$, $d 3$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$) ($\phi 4$, $d 3$)	
	0.26	58	0.26	7	0.46	9	0.57	116	0.52	15	0.52	106
Smaller defects SSL316 20 Defects	($\phi 4$, $d 1$), ($\phi 3$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$) ($\phi 4$, $d 3$), ($\phi 3$, $d 3$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$), ($\phi 2$, $d 2$)	
	0.18	66	0.18	7	0.46	10	0.57	62	0.4	17	0.46	72
Smaller defects INC718 20 Defects	($\phi 4$, $d 1$), ($\phi 3$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$)		($\phi 4$, $d 1$), ($\phi 3$, $d 1$) ($\phi 2$, $d 1$), ($\phi 4$, $d 2$) ($\phi 3$, $d 2$)	
	0.18	64	0.18	7	0.26	9	0.26	108	0.26	27	0.33	116

Figure 14 – Benchmarking of ICA, PCA, NLBSS, STBSS, SDL, and STSDL algorithms performance in detection of imprinted flaws in SSH36 (high porosity), SSL316 (low porosity), and INC718 specimens [23]. The larger and smaller defect patterns contain a total of 12 and 20 imprinted defects, respectively. Performance of the algorithms was ranked by the F-score (values between 0 and 1) and execution run time (measured in seconds). The largest value of F-score for each AM specimen and defect pattern is indicating by highlighting (color on-line).

The runtime of algorithms in Figure 14 is measured in seconds. Detected defects for each entry in Figure 14 are listed as a set of numbers (ϕ , d), where ϕ is the defect diameter and d is its depth, all measured in mm (see Figure 11). All benchmarking studies were performed on Intel (R) Core (TM) i7-8750H, CPU@2.20GHz 2.21GHz computer with 16GB RAM.

In general, internal defects with smaller diameter and deeper location are more difficult to detect. The reason is that defects of smaller size have smaller thermal resistance visible on the plate surface because heat can diffuse around these defects. In addition, thermal resistance of defects located deeper below the surface manifests itself when surface temperature has decayed to the level close to the ambient temperature. These factors result in low thermal contrast “hot spots” on the specimen surface, which are difficult to detect. Further improvements in flash thermography hardware and ML algorithms would be needed to detect smaller and deeper-located defects. When

comparing the materials, detection is generally better for SSH316, followed by SSL316 and INC718. This can be understood from the fact that SS316 has higher thermal diffusivity than INC718, and from higher thermal resistance contrast in high porosity SSH316 compared to low porosity SSL316.

The STBSS and STSDL methods have similar performance results, which is better than those of other ML algorithms considered in this study. The F-score of STBSS is slightly better for smaller defects, while the F-score of STSDL is slightly better for larger defects. The increase in accuracy is accomplished at the expense of increasing run time. For both STBSS and STSDL the runtime can be on the order of 100s. This is the time to process images for material section with dimensions of approximately 76mm×76mm×10mm. Additional time of approximately 10s to acquire images with flash thermography should be added to estimate the total time. For a structure with dimensions of 22.8cm×22.8cm×10mm, for example, the total processing time would be approximately 1000s or approximately 17min. In principle, this reasonable time for implementing QC for low-volume AM of structures. Processing time can be further reduced by using more powerful computing resources.

4. Thermal Tomography Imaging with Compact Infrared Camera

The objective of this section is to investigate NDE of AM metallic structures with an imaging system based on relatively low-cost and small form factor IR cameras with uncooled microbolometer detectors. In this section, TT reconstructions are obtained for AM SS316L plate with imprinted internal porosity defects of variable sizes. Thermography images obtained with a compact IR cameras have lower quality, as compared to those obtained with high-end cooled semiconductor IR camera, because of lower sensitivity, lower sampling rate, and strong noises of small IR camera. We demonstrate that reduction in image quality can be partially compensated with machine-learning based image de-noising algorithms. We model IR camera noises using Additive white Gaussian noise (AWGN) model. In principle, AWGN can be removed from images with a Gaussian filter, but this leads to image blurring. We show that quality of images is enhanced using Sparse Coding (SC) and K-means Singular Value Decomposition (K-SVD) ML algorithms, which remove AWGN without blurring the images.

4.1. Machine learning-based image de-noising

Because of significant amount of noise in compact microbolometer-based IR camera, imaging contrast is lower than that obtained with high-end IR camera. As can be seen from Equation (13), reconstruction accuracy depends on the surface temperature sampling rate. Thus, relatively slow frame rate and detector integration time of A65 camera degrades image quality as well. In this paper, we develop ML-based image de-noising algorithm to partially compensate for strong noises in images acquired with small IR camera. We model IR camera noise as Additive white Gaussian noise (AWGN), which is a basic noise model of many random processes. In principle, AWGN can be removed from an image with a Gaussian filter. However, this results in image blurring. We use the Sparse Coding (SC) with K-means Singular Value Decomposition (K-SVD) ML-based algorithm to remove AWGN noise in TT reconstruction images obtained with a compact FLIR A65 camera without blurring the image. The flow diagram of the SC/K-SVD algorithms is shown in Figure 15 [24]. The details of the algorithm implementation are discussed in the following sub-sections.

Figure 15 – Flow chart of the SC/K-SVD algorithm [24].

4.1.1. Sparse coding de-noising

SC method aims to find the sparse representation of data by searching for the optimized basis vectors of dictionary [48]. In SC method, the dictionary includes the optimized basis vectors called atoms, which are linearly combined to represent image information. Compared to the commonly used Principal Component Analysis (PCA) method [25,45,51], SC allows more flexibility in images de-noising as the atoms are not required to be orthogonal. Compared to deep learning methods, such as convolutional neural networks (CNN) [52], training SC model requires less time and fewer computations. The objective function of the SC algorithm is modeled as:

$$\underset{D, X}{\text{minimize}} \|Y - (DX)\|_F^2 + \lambda \|X\|_0, \quad (24)$$

where Y represents the matrix of images for training the SC model, D and X are the dictionary and representation matrices, respectively. Thus, the first term in Equation (24) that measures the difference between training images Y and reconstruction images (DX) models the noisy information, which is minimized to de-noise the thermography data. Here the difference is measured by the least squares approximation with the Frobenius norm. The second term imposes the constraint of sparse representation regularized by the ℓ_0 normalization. Here λ is a scaling constant that determines the tradeoff between the de-noising and representation sparsity. We

trained the SC model using the K-means Singular Value Decomposition (K-SVD) algorithm [53] to iteratively update the dictionary matrix D for de-noising TT images.

4.1.2. K-means Singular Value Decomposition (K-SVD)

The K-means Singular Value Decomposition (K-SVD) was used to create the dictionary for sparse representation of the TT images. The K-means clustering and Singular Value Decomposition [53] are combined to update the representation and dictionary matrices X and D to minimize noise in images. There are two stages to implement the K-SVD algorithm. In the 1st stage, the dictionary matrix $D \in R^{N \times K}$ is fixed and initialized randomly for estimating the representation matrix X by minimizing the objective function in Equation (24). This problem was solved by using the matching pursuit algorithm [54]. In the 2nd stage, the estimated representation matrix X is used to search for a better dictionary matrix D by minimizing the objective function. Each atom d_k , which is the k^{th} column of the dictionary matrix D , is optimized to iteratively update the whole dictionary. This problem was solved by using the K-means clustering and the SVD

4.2. Development of AM SS316L plates with imprinted regions of porosity

Calibrated defects with hemispherical shape were imprinted into SS316L specimen to study TT performance in detection of material flaws. While pores in AM metals can have a variety of shapes, the spherical shape of the calibrated defect provides a generic representation of material flaw. For studying thermal tomography performance, either hemispherical or spherical shape defects provide similar target characteristics. A stainless steel SS316L plate was fabricated with direct metal laser melting (DMLM) method using EOS metal 3D printer (GPI Prototyping and Manufacturing). DMLM, also known as direct metal laser sintering (DMLS) is one of the methods in the LPBF category of AM processes. Fabrication of SS316L plate was based on 20 μm powder layers. The dimensions of the plate are Length $\times$ Width $\times$ Thickness: 6in $\times$ 3in $\times$ 0.4in (152mm $\times$ 76mm $\times$ 10mm).

A pattern of calibrated defects consisting of hemispherical porosity regions containing unsintered metallic powder were imprinted into the SS316L plates. The defects were imprinted into the plates during fabrication using an STL (sterelithography) file with a drawing of the pattern of hemispherical inclusions. A computer rendering of the pattern of defects is shown in Figure 16(a) [24]. Drawings with labels showing diameters and depths of the imprinted defects are shown in Figs. 16(b) and 16(c). The depth of a defect is defined as the distance from the surface of the plate to the top of the curved face of the hemispherical inclusion. Note that there are two patterns of defects in the plate: one with diameters $\phi = 5, 6$ and 8mm and depths $d = 2, 3, 4$, and 5mm, and another one with diameters $\phi = 1, 2, 3$, and 4mm and depths $d = 1, 2, 3, 4$ and 5mm. The two patterns are indicated by red wireframe boxes in Figures 16(b) and 16(c), respectively. The diameters of defects decrease along the lines parallel to the longer side of the plate, while the depth along these lines is held constant. Along the lines parallel to the shorter side of the plate, the depth increases, while the diameter is fixed along these lines. For hemispherical-shape defects, the ratio of characteristic lateral and transverse dimensions is unity. As discussed in Section 2.3, diffusion

of heat around defect boundaries is expected to have a negative impact on visibility of defects in TT reconstructions.

(a)

(b)

(c)

Figure 16 – (a) 3D rendering of hemispherical porosity defects imprinted in AM specimens. (b) and (c) Design pattern of hemispherical defects of different diameters and depths relative to plate surface (all dimensions are in mm). Red wireframe boxes indicate (b) larger defects pattern and (c) smaller defects pattern [24].

4.3. Imaging of imprinted porosity defects in SS316L plates with A65 FLIR camera

The photograph of the laboratory systems displayed in Figure 17 [24]. As in the system shown in Figure 2, material is illuminated with white light flash lamp, which rapidly deposits heat on the material surface. In the experiment, a Balcar ASYM 6400 white light flash lamp delivers 6400MW of power in approximately 2ms duration flash. A pulse trigger sends a signal to capacitor to discharge in a circuit containing white light flash lamp. A megapixel fast frame infrared (IR) camera records time-resolved images of surface temperature distribution $T(x,y,t)$. The acquired thermal-imaging data cube therefore consist of a series of 2D images of the sample's surface temperature at consecutive time instants. The laboratory system shown in Figure 17 uses a compact low-cost A65 FLIR camera, which has dimensions (L x W x H) of 4.1 x 1.9 x 1.8 in (295 x 200 x 105 mm). The detector is a focal plane array (FPA) uncooled Vanadium Oxide (VOX) microbolometer, which operates in the spectral range 7.5 – 13 μ m with noise equivalent temperature detection (NETD) of 50mK and 12ms time constant. The camera has spatial resolution

of 640 x 512 pixels with 30Hz imaging frame rate. The focal length of the camera lens is 13mm, resulting in imaging resolution of approximately 140 μ m per pixel. The total area of the image is 9cm x 7.2cm. Performance specifications of A65 FLIR camera are inferior to those of cooled semiconductor IR cameras, such as FLIR indium antimonide (InSb) detector x8501sc camera shown in Figure 2. The latter has detector integration time of 270ns, NETD sensitivity of <30mK, and frame rate of at least 180Hz. Note that in future designs, a flash lamp in Figure 17 could be replaced with a smaller size flash lamp or a laser to make the entire system compact.

Figure 17 – Experimental laboratory setup with compact A65 FLIR camera [24].

Using TT set up shown in Figure 17, we obtained images of porosity defects imprinted in SS316L plate. Imaging was performed with plate oriented in way that the hemispherical sides of the internal defects were facing the IR camera and flash lamp. Separate measurements were made imaging larger and smaller defects patterns. Grayscale images of reconstruction of the larger and smaller defects patterns are shown in Figures 18 and 19, respectively. Corresponding maps of these defects patterns are shown in Figures 16(b) and 16(c), respectively. Reconstruction images shown in Figures 18 and 19 contain the largest number of detected defects in respective pattern. Figures 18 and 19 also display de-noised TT reconstruction images in corresponding sub-panels. Noise removal is accomplished by blurring images with MATLAB 2D Gaussian filter with $\sigma = 1$ [31], and by using SC/K-SVD algorithm.

TT reconstruction of larger defects pattern at depth $z = 3\text{mm}$ is shown in Figure 18(a) [24]. Note that defects $(d2, \phi8)$, $(d2, \phi6)$, $(d2, \phi5)$, $(d3, \phi8)$, and $(d3, \phi8)$ are visible. Gaussian-filtered image with AWGN removed from TT reconstruction is displayed in Figure 18(b). Compared to TT reconstruction in Figure 18(a), Gaussian-filtered image in Figure 18(b) has less noise at the expense of image blurring. The dictionary matrix used in SC/K-SVD algorithm is displayed in Figure 18(c). The image in Figure 18(d) shows TT reconstruction with AWGN removed using SC/K-SVD method. Compared to Figures 18(a) and 18(b), the image in Figure 18(d) has decreased noise and sharper features.

Figure 18 – Imaging of larger pattern of porosity defects in SSL316 plate [24]. (a) TT reconstruction grayscale image of $e(x,y)$ at $z = 3\text{mm}$ depth. (b) Gaussian-filtered TT reconstruction image with AWGN removed. (c) Dictionary matrix in SC/K-SVD algorithm. (d) TT reconstructions with AWGN removed using SC/K-SCD method.

Grayscale images of reconstruction of the smaller pattern of defects, as shown in Figure 17(b), are displayed in Figure 19 [24]. TT reconstruction at depth $z = 1\text{mm}$ is shown in Figure 19(a). Note that defects $(d1, \phi4)$, $(d1, \phi3)$, and possibly $(d1, \phi2)$ are visible. Gaussian-filtered image with AWGN removed from TT reconstruction is displayed in Figure 19(b). Compared to TT reconstruction in Figure 19(a), Gaussian-filtered image in Figure 19(b) has less noise at the expense of image blurring. The dictionary matrix used in SC algorithm is displayed in Figure 19(c). The image in Figure 19(d) shows TT reconstruction with AWGN removed using SC/K-SVD method. As in Figure 18, compared to Figures 19(a) and 19(b), the image in Figure 19(d) has less noise and appears sharper. Note that the smallest clearly visible defect detected with A65 FLIR camera after AWGN removal is $(d2, \phi3)$. In comparison, when using high-end X8501sc FLIR camera, the smallest detected defect in the same SS316L specimen is $(d1, \phi1)$ [21-24].

Figure 19 – Imaging of smaller defects in SS316L plate (a) TT reconstruction grayscale image of $e(x,y)$ at $z = 1\text{mm}$ depth. (b) Gaussian-filtered TT reconstruction image with AWGN removed. (c) Dictionary matrix in SC/K-SVD algorithm. (d) TT reconstructions with AWGN removed using SC/K-SCD method [24].

To quantify de-noising performance of the SC/K-SVD method, we calculate peak signal-to-noise ratio (PSNR) for the images in Figure 18 and Figure 19. PSNR is calculated for TT reconstructions (Figures 18(a) and 19(a)) and SC/K-SVD de-noised images (Figures 18(d) and 19(d)) using Gaussian-filtered images (Figures 18(b) and 19(b)) as baseline references. PSNR is calculated as:

$$PSNR = 10 \log_{10} \left(\frac{1}{MSE} \right) \quad (25)$$

Where the MSE stands for the mean squared error between the respective images and Gaussian-filtered reference. The values of PSNR are summarized in Table 2, where PSNR TT and PSNR K-SVD are the labels for TT reconstructions and K-SVD de-noised images. From the data in Table 2, one can observe that PSNR K-SVD is substantially larger than that of un-processed TT reconstruction for both large and small defects.

Table 2 – PSNR calculated for TT and K-SVD de-noised images

	PSNR TT (dB)	PSNR K-SVD (dB)
Large Defects	17.17	22.41
Small Defects	19.74	28.31

4.4. Preliminary Analysis of Operating Environment for In-Service NDE with Thermal Tomography

Following initial qualification of an AM component for deployment in a nuclear reactor, a compact TT can also be used for in-service nondestructive evaluation (NDE). With capability to perform in-service NDE of the AM component lifecycle, TT data can be used for development of a component *digital twin*. MIT research reactor (MITR) has been identified as a representative environment to perform investigation of feasibility of in-service NDE during shutdown. Preliminary study of radiation level in the MITR viewport, with geometric parameters potentially compatible with compact TT system, has been conducted. MIT research reactor (MITR) provides a representative environment for evaluating performance of compact TT system performance for in-service NDE applications. In the cutaway view of MITR diagram shown in Figure 20 [55], the 3GV vertical viewport with 3in inner diameter (ID) is compatible with a compact TT system based on A65 FLIR camera.

Figure 20 – 3GV viewport with 3in ID vertical irradiation thimbles [55].

Challenges to in-service NDE during reactor shutdown include delayed neutron and gamma radiation from fuel, which could adversely affect IR camera performance. Preliminary analysis of the environment in 3GV viewport was conducted by measuring gamma-ray dose during the shutdown in the beam-port. A sketch of the experimental setup is shown in Figure 21 [56]. Position #1 is at the level of the reactor core, while positions #3 and #4 are above the core, and are located

22in and 38in above position #1, respectively. Additional measurement was taken on the reactor deck.

Figure 21 – Measurement of gamma-ray dose inside 3GV viewport [56].

Results of measurements are shown in Table 3. The detector could only measure up to 15,000 R/h, and often the dose was higher. Next steps will involve testing the IR camera when the dose is below 15 kR/h, since little is known about the survival of these cameras in radiation fields.

Table 3 – Measurement of gamma-ray dose inside 3GV tube

Date	Position #1 GM	#3 GM	#4 GM	@ deck GM	@deck Ion Chamber
10/4/2019	> 15 kR/h	> 15 kR/h	7000 R/h	2.5 R/h	1.8 R/h
10/7/2019	> 15 kR/h	14,300 R/h	4200 R/h		0.45 R/h
10/15/2019	> 15 kR/h	13,800 R/h	2,600 R/h		0.22 R/h
10/18/2019	> 15 kR/h	> 15 kR/h	> 15 kR/h		0.3 R/h

5. Conclusions

Additive manufacturing (AM) offers the potential of reduced-cost manufacturing of structures for nuclear energy applications. Laser powder bed fusion (LPBF) is a common method for AM of stainless steel 316L (SS316L) and similar high-strength corrosion-resistant metals and alloys used for passive structures in nuclear energy application. However, common defects appearing in structures manufactured with LPBF include porosity regions. Quality control of AM structures is needed before their deployment in the harsh environment of a nuclear reactor. Thermal tomography (TT) method provides non-destructive capability to image actual structures.

The imaging method uses data cube of surface temperature transients $T(x,y,t)$ measured with flash thermography to reconstruct 3D spatial effusivity $e(x,y,z)$. Thermal tomography provides the capability to image AM structures made from corrosion-resistant high-strength IN718 and SS316L alloys, which are frequently used in nuclear energy applications. Such capability is need for shape validation during manufacturing, and on-line and off-line nondestructive evaluation of AM structures. We have described the details of thermal tomography algorithm, which was studied with COMSOL computer simulations. Thermal tomography 3D imaging was demonstrated for a complex shape IN718 structure produced with LPBF method. Next, 3D imaging with thermal tomography of SS316L plate containing flat bottom hole (FBH) indentations was investigated. The diameters of the defects varied from 1mm to 4mm, and their depths below the surface varied from 1mm to 5mm. Because the FBH's offer higher thermal diffusivity contrast compared to imprinted defects, the specimen with FBH's was used for initial thermal tomography performance evaluation. Finally, an IN718 plate was fabricated with LPBF method, which contained imprinted defects which were created in the form of hemispherical shape inclusions with trapped un-sintered powder. The same pattern and dimensions of internal defects as in the FBH plate were introduced into the AM plate. Thermal tomography was used for 3D imaging of imprinted defects in the IN718 plate. The smallest defect detected with thermal tomography was an imprinted hemisphere with $\phi = 1\text{mm}$ diameter located at $d = 1\text{mm}$ depth.

In general, internal defects with smaller diameter and deeper location are more difficult to detect. The reason is that defects of smaller size have smaller thermal resistance, and hence less visible on the plate surface because heat can diffuse around these defects. In addition, thermal resistance of defects located deeper below the surface manifests itself when surface temperature has decayed to the level close to the ambient temperature. These factors result in low thermal contrast "hot spots" on the specimen surface, which are difficult to detect when the contrast approaches noise equivalent temperature difference (NETD) threshold of the IR camera. The effective detection depth of defects in AM metallic specimens with thermal tomography is currently under investigation. In general, smaller defects are detected when they are closer to the surface. Computer simulations indicate that at 1mm depth below the surface, defects down to 50 μm diameter size can be detected. Using a using high-end cooled semiconductor detector camera, we have demonstrated detection of imprinted 1mm-diameter defects located at 1mm depth in SS316L and IN718 AM specimens. Ongoing work is investigating detection of smaller defects located closer to the surface. However, detection capabilities of thermal tomography should also

be viewed in the context of potential of the pore to be a seed for crack initiation. Studies in literature on fatigue cracking of AM metals suggest that pores that are larger and closer to the surface are more likely to cause fatigue crack initiation.

In this paper, we have investigated detection of imprinted regions of porosity defects in AM SS316L specimen using TT system, in which imaging data is obtained with a compact and relatively low-cost infrared (IR) camera. Using such camera is advantageous for cost-reduction of the manufacturing and qualification process, as well for imaging complex geometry AM structures with spatially constrained access. However, small form factor IR camera, which is typically based on an uncooled microbolometer detector, has lower sensitivity, integration time, and sampling rate compared to high-end cooled semiconductor detector IR camera. This results in higher noise and lower detection sensitivity in thermography images obtained with a compact IR camera. In this paper, we develop machine learning (ML) sparse coding (SC) K-means singular value decomposition (K-SVD) method for partially compensating for reduced quality of thermography images through reduction of noise. IR camera noise is modeled as Additive white Gaussian noise (AWGN), which is a commonly used model of noise caused by a variety of random processes.

Using FLIR A65 compact camera, we have obtained TT reconstructions of sub-surface defects consisting of hemispherical-shape un-sintered powder regions imprinted into SS316L specimen during manufacturing. The smallest clearly visible defect is located at 1mm depth and has diameter of 3mm. Our results show that the SC/K-SVD algorithm removes the AWGN from TT images. In general, internal defects with smaller diameter and deeper location are more difficult to detect. The reason is that defects of smaller size have smaller thermal resistance visible on the plate surface because heat can diffuse around these defects. In addition, thermal resistance of defects located deeper below the surface manifests itself when surface temperature has decayed to the level close to the ambient temperature. Further improvements in thermography hardware and ML algorithms would be needed to detect smaller and deeper-located defects, such as increasing the power of the flash lamp, or adding a second flash. In addition, possible improvement of imaging can be obtained by developing more elaborate models of IR camera noises, and training ML to improve their de-noising performance. Preliminary analysis of radiation background in 3GV viewport of MITR was conducted during reactor shutdown to evaluate feasibility of in-service NDE in this environment with compact TT system. Next steps will involve testing the IR camera when the dose is below 15 kR/h, since little is known about the survival of these cameras in radiation fields.

Further improvements in thermography hardware and ML algorithms would be needed to detect smaller and deeper-located defects, such as increasing the power of the flash lamp, and using a microscopic lens to increase the number of pixels per an image of a defect could enhance detection resolution. In addition, possible improvement of imaging can be obtained by developing more elaborate models of IR camera noises, and training ML to improve their de-noising performance.

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