Development of Thermal Tomography Imaging System for In-Service Nondestructive Evaluation of Additively Manufactured Components

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

Nuclear Science and Engineering Division

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prepared by
Alexander Heifetz¹, Xin Zhang^{1,2}, Jafar Saniie², Boris Khaykovich³

¹Nuclear Science Engineering Division, Argonne National Laboratory

²Department of Electrical and Computer Engineering, Illinois Institute of Technology, Chicago, IL

³Nuclear Reactor Laboratory, Massachusetts Institute of Technology, Cambridge, MA

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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. 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*. 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.

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 alloys, such as stainless steel 316/316L (SS316L). Because of high strength (200GPa Young's modulus at room temperature), 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]. Because of the intrinsic features of LPBF, e.g. Marangoni convection, material defects such as porosity and anisotropy can appear in the metallic structure [5]. Porosity can be introduced into AM parts due to incomplete melting of the powder particles or insufficient overlapping of the melt pools [6]. 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 [7]. Furthermore, improper cooling rates can cause the formation of non-equilibrium phases and residual stresses, requiring post-process heat treatments [8,9].

Figure 1 – Overview of SLM: (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

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. Presence of porosity material defects could potentially combine with fatigue of AM metallic structure [10,11] due to long-term exposure to high temperature and ionizing radiation to decrease structure service life. 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 porosity material defects [12,13].

Thermography is a potentially promising non-destructive evaluation (NDE) approach to quality control of fabricated AM structures [14-17]. 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. Alternative approaches to quality control of AM structures could utilize NDE techniques, such X-ray radiography [18] 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, this provides sampled information about the quality of the AM process, but not about the actual structure. 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.

The objective of this report 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. Thermal tomography (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.

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.

2. Thermal Tomography Imaging and Machine Learning-Based Image De-Noising

2.1. Flash thermography imaging system

Thermographic imaging method described in this report is thermal tomography (TT), which is a computational method for reconstruction and presentation of data obtained from flash thermography measurements [19-21]. 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 $T(x,y)$. 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 $e(x,y,z)$. Images of effusivity can be used to characterize material flaws. In general, high resolution thermography imaging requires using expensive IR cameras utilizing cooled semiconductor detectors, which would raise the overall cost of the AM process. Aside from cost-savings, using compact IR cameras has advantages for NDE of complex shape structures, because smaller cameras can be inserted into spatially constrained spaces. While compact cameras, in general, have lower sensitivity and larger noise, recent advances in machine learning (ML) algorithms for image processing can partially compensate for loss in imaging quality.

A schematic depiction of the flash thermography setup is shown in Figure 2(a), with the photograph of the laboratory systems displayed in Figure 2(b). The method consists of illuminating material 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 Fig. 3(c) 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. Performance specifications of A65 FLIR camera are inferior to those of cooled semiconductor IR cameras, such as FLIR indium antimonide (InSb) detector x8501sc camera [19-21]. The latter has detector integration time of 270ns, NETD sensitivity of <30mK, and frame rate of at least 180Hz.

For better absorption of thermal energy, all specimens were spay-painted with washable graphite paint. 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. Note that in future designs, a flash lamp in Figure 2(b) could be replaced with small form factor flash lamp a laser to make the entire system compact.

Figure 2 – (a) Schematics of flash thermography setup. (b) Experimental laboratory setup with compact A65 FLIR camera (bottom).

2.2. Thermal tomography imaging of SS316L structures

The reconstruction algorithm of TT obtains thermal effusivity $e(x,y,z)$ from time-dependent surface temperature $T(x,y,t)$ measurements [21]. The model assumes that heat propagation is one-dimensional along the z -coordinate. 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) . Thermal effusivity is defined as

$$e = \sqrt{\rho ck} . \quad (3)$$

Following instantaneous deposition of energy on the material surface, heat diffuses into the material bulk. One can obtain the relationship between thermal wavefront depth inside the material z and time t after heat deposition as

$$z = \sqrt{\pi \alpha t} . \quad (4)$$

Using the analytic solution of Equation (1) for semi-infinite slabs, one can obtain the apparent effusivity as function time $e(t)$, which with the help of Equation (4) can be transformed to be function of depth $e(z)$, given as [21]

$$e(z) = z \frac{2Q}{\pi \sqrt{\alpha}} \frac{d}{dt} \left(\frac{1}{T(t)} \right) \bigg|_{t=z^2/\pi\alpha} , \quad (5)$$

where Q is the instantaneously deposited surface thermal energy density. This shows that spatial reconstruction of 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 (4). Thus, the matrix $e(x,y,z)$ is obtained through a linear transformation of the matrix $T(x,y,t)$.

Information about material internal structure is contained in surface temperature transients surface temperature $T(x,y,t)$ measurements, and correspondingly in $e(x,y,z)$, because thermal resistance of internal structures affects local surface temperature decay rate. For example, pores have lower thermal diffusivity compared to the rest of the solid material. This results in slower surface temperature decay in regions above the defects, and appearance of local temperature “hot spots.” Information obtained from thermography measurements is relative, but can be converted to absolute scale through calibration. In this paper, we display reconstructed effusivity as grayscale images of $e(x,y)$ at depths z .

To estimate maximum contrast in grayscale images of TT reconstructions, we calculate effusivities of porosity regions. According to random close packing (RCP) model, for monodispersed spheres poured onto bed, the maximum void fraction is $\varepsilon=0.35$, with corresponding or packing density $\eta=0.65$ [22]. A similar value of ε was arrived at from experimental measurements of SS316L powder with the average powder particles diameter of $35\mu\text{m}$ [23]. Using the values of SS316L solid density ρ_s and heat capacity c_s at room temperature from [24], we calculated density ρ_p and heat capacity c_p of powder as $\rho_p = \eta \rho_s$ and $c_p = \eta c_s$. The value of thermal conductivity $k_p = 0.2 \text{ W/m}^2\text{K}$ for SS316L is taken from [23]. Thermophysical properties of solid and powder SS316L are displayed in Table 1, along with calculated values of thermal diffusivity and effusivity. From Table 1, the ratio of solid to powder effusivity is $e_s/e_p = 13$. This value gives the theoretically expected grayscale intensity contrast in the reconstructed effusivity images for layered media. For defects with finite transverse dimension, lateral heat diffusion in solid media

around the boundary of the defect is expected to decrease imaging contrast. Equation (4) can be used to derive the approximate criteria when the layered media approximation is satisfied. For example, for a cylindrical defect with dimension r in the x - y plane and thickness z , and thermal diffusivities α_s and α_p of solid and powder, the criterion can be written as

$$t_z = z^2 / \pi \alpha_p \gg t_r = r^2 / \pi \alpha_s \quad (6)$$

From which we can obtain

$$r/z \ll \sqrt{\alpha_s / \alpha_p} \quad (7)$$

Using the values listed in Table 1, we obtain the approximate criterion as $r/z \ll 5$.

Table 1 – Thermophysical parameters of SS316L solid and powder media

Medium	ρ (kg/m ³)	c (J/kg)	k (W/m*K)	α (mm ² /s)	e (J/m ² *K*s ^{1/2})
Solid	7954	499.07	13.96	3.52	7444
Powder	5091	319.4	0.2	0.123	570

2.3. Machine learning-based image processing

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 (5), 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) ML-based algorithm to remove AWGN noise in TT reconstruction images obtained with a compact FLIR A65 camera without blurring the image.

2.3.1. Sparse coding de-noising

SC method aims to find the sparse representation of data by searching for the optimized basis vectors of dictionary [25]. 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 [26-28], 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) [29], training SC model requires less time and fewer computations. The objective function of the SC algorithm is modeled as:

$$\text{minimize}_{D,X} \|Y - (DX)\|_F^2 + \lambda \|X\|_0, \quad (8)$$

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 (8) 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 [30] to iteratively update the dictionary matrix D for de-noising TT images.

2.3.2. 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 [30] 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 (8). This problem was solved by using the matching pursuit algorithm [31]. 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.

3. Thermal Tomography Imaging of Internal Defects in Additively Manufactured Stainless Steel 316L

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

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 μ m 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 un-sintered 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 3(a).

(a)

(b)

(c)

Figure 3 – (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.

Drawings with labels showing diameters and depths of the imprinted defects are shown in Figures 3(b) and 3(c). 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 3(b) and 3(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 2.2, diffusion of heat around defect boundaries is expected to have a negative impact on visibility of defects in TT reconstructions.

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

Using TT set up shown in Figure 2, 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 4 and 5, respectively. Corresponding maps of these defects patterns are shown in Figures 3(b) and 3(c), respectively. Reconstruction images shown in Figures 4 and 5 contain the largest number of detected defects in respective pattern. Figures 4 and 5 also display de-noised TT reconstruction images in corresponding sub-panels. Noise removal is accomplished by blurring images with MATLAB 2D Gaussian filter with $\sigma=1$ [27], and by using SC/K-SVD algorithm.

TT reconstruction of larger defects pattern at depth $z = 3\text{mm}$ is shown in Figure 4(a). 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 4(b). Compared to TT reconstruction in Fig 3(a), Gaussian-filtered image in Figure 4(b) has less noise at the expense of image blurring. The dictionary matrix used in SC/K-SVD algorithm is displayed in Figure 4(c). The image in Figure 4(d) shows TT reconstruction with AWGN removed using SC/K-SVD method. Compared to Figures 4(a) and 4(b), the image in Figure 4(d) has decreased noise and sharper features.

Figure 4 – Imaging of larger pattern of porosity defects in SSL316 plate. (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 3(b), are displayed in Figure 5. TT reconstruction at depth $z = 3\text{mm}$ is shown in Figure 5(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 5(b). Compared to TT reconstruction in Figure 5(a), Gaussian-filtered image in Figure 5(b) has less noise at the expense of image blurring. The dictionary matrix used in SC algorithm is displayed in Figure 5(c). The image in Figure 3(d) shows TT reconstruction with AWGN removed using SC/K-SVD method. As in the case for Figure 4, compared to Figures 5(a) and 5(b), the image in Figure 5(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 $(d1, \phi1)$ [19-21].

Figure 5 – 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.

To quantify de-noising performance of the SC/K-SVD method, we calculate peak signal-to-noise ratio (PSNR) for the images in Figures 4 and 5. PSNR is calculated for TT reconstructions (Figures 4(a) and 5(a)) and SC/K-SVD de-noised images (Figures 4(d) and 5(d)) using Gaussian-filtered images (Figures 4(b) and 5(b)) as baseline references.

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

PSNR is calculated as:

$$PSNR = 10 \log_{10} \left(\frac{1}{MSE} \right) \quad (9)$$

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.

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

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 6, the 3GV vertical viewport with 3in inner diameter (ID) is potentially compatible with a compact TT system based on A65 FLIR camera.

Figure 6 – 3GV viewport with 3in ID vertical irradiation thimbles [32].

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 7. 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 7 – Measurement of gamma-ray dose inside 3GV viewport

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.

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 denoising 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.

References

1. T. DebRoy, H.L. Wei, J.S. Zuback, T. Mukherjee, J.W. Elmer, J.O. Milewski, A.M. Beese, A. Wilson-Heid, A. De, W. Zhang, “Additive manufacturing of metallic components – Process, structure and properties,” *Progress in Material Science* 92, 112-224 (2018).
2. X. Lou and D. Gandy, “Advanced manufacturing for nuclear energy,” *JOM* 71, 2834-2836 (2019).
3. S.A. Khairallah, A.T. Anderson, A. Rubenchik, W.E. King, “Laser powder-bed fusion additive manufacturing: Physics of complex melt flow and formation mechanisms of pores, spatter, and denudation zones,” *Acta Materialia* 108, 36-45 (2016).
4. W.E. King, A.T. Anderson, R.M. Ferencz, N.E.Hodge, C. Kamath, S.A. Khairallah, and A.M. Rubenchik, “Laser powder bed fusion additive manufacturing of metals: physics, computational and materials challenges,” *Appl. Phys. Rev.* 2, 041304 (2015).
5. Y. Kok, X.P. Tan, P. Wang, M.L.S. Nai, N.H. Loh, E. Liu, S.B. Tor, “Anisotropy and heterogeneity of microstructure and mechanical properties in additive manufacturing: A critical review,” *Materials and Design* 139, 565-586 (2018).
6. R. Cunningham, R., Narra, S. P., Montgomery, C., J. Beuth, and A.D. Rollett, “Synchrotron-based X-ray microtomography characterization of the effect of processing variables on porosity formation in laser power-bed additive manufacturing of Ti-6Al-4V,” *JOM*, 69(3), 479-484, 2017.
7. C. Zhao, K. Fezzaa, R.W. Cunningham, H. Wen, F. De Carlo, L. Chen, A.D. Rollett, and T. Sun, “Real-time monitoring of laser powder bed fusion process using high-speed X-ray imaging and diffraction,” *Scientific Reports*, 7(1), 3602 (2017).
8. W.J. Sames, F.A. List, S. Pannala, R.R. Dehoff, and S.S. Babu, “The metallurgy and processing science of metal additive manufacturing,” *International Materials Reviews*, 61(5), 315-360 (2016).
9. J.J. Lewandowski, & M. Seifi, “Metal additive manufacturing: a review of mechanical properties,” *Annual Review of Materials Research*, 46, 151-186 (2016).
10. A.B. Spierings, T.L. Starr, K. Wegener, “Fatigue performance of additive manufactured metallic parts,” *Rapid Prototyping Journal* 19(2), 88-94 (2013).
11. S. Tammas-Williams, P. J. Withers, I. Todd, and P.B. Prangnell, “The influence of porosity on fatigue crack initiation in additively manufactured titanium components,” *Scientific Reports* 7, 7308 (2017).
12. D. Kong, C. Dong, X. Ni, X. Li, “Corrosion of metallic materials fabricated by selective laser melting,” *Nature Materials Degradation* 3(24), 1-13 (2019).
13. G. Sander, J. Tan, P. Balan, O. Gharbi, D.R. Feenstra, L. Singer, S. Thomas, R.G. Kelly, J.R. Scully, and N. Birbillis, “Corrosion of additively manufactured alloys: A review,” *Corrosion* 74(12), 1318-1350 (2018).
14. S.D. Holland and R.S. Reusser, “Material evaluation by infrared thermography,” *Annual Reviews of Materials Research* 46, 287-303 (2016).

15. J.E. Siegel, M.F. Beemer, S.M. Shepard, "Automated non-destructive inspection of Fused Filament Fabrication components using Thermographic Signal Reconstruction," *Additive Manufacturing* 31, 100923 (2020).
16. Q.Y. Lu and C.H. Wong, "Application of non-destructive testing techniques for post-process control of additively manufactured parts," *Virtual and Physical Prototyping* 12(4), 301-321 (2017).
17. Q. Luo, B. Gao, W.L. Woo, Y. Yang, "Temporal and spatial deep learning network for infrared thermal defect detection," *NDT&E International* 108, 102164 (2019).
18. A. Thompson, I. Maskery, R. Leach, "X-ray computed tomography for additive manufacturing: A review," *Measurement Science and Technology* 27, 072001 (2016).
19. A. Heifetz, D. Shribak, T. Liu, T.W. Elmer, P. Kozak, S. Bakhtiari, B. Khaykovich, W. Cleary, "Pulsed thermal tomography nondestructive evaluation of additively manufactured reactor structural materials," *Transactions of the American Nuclear Society* 121(1), 589-591 (2019).
20. X. Zhang, J. Saniie, A. Heifetz, "Quality control of additively manufactured metallic structures with machine learning of thermography images," submitted to JOM (2020).
21. A. Heifetz, D. Shribak, X. Zhang, J. Saniie, T. Liu, J.G. Sun, T. Elmer, S. Bakhtiari, W. Cleary, "Thermal tomography 3D imaging of additively manufactured metallic structures," submitted to *AIP Advances* (2020).
22. H.M. Jaeger and S.R. Nagel, "Physics of granular states," *Science* 255(5051), 1523–1531 (1992).
23. L.C. Wei, L.E. Ehrlich, M.J. Powell-Palm, C. Montgomery, J. Beuth, J.A. Malen, "Thermal conductivity of metal powders for powder bed additive manufacturing," *Additive Manufacturing* 21, 201-208 (2018).
24. C.S. Kim, "Thermophysical properties of stainless steels," ANL-75-55 (1975).
25. J. Mairal, F. Bach, J. Ponce, G. Sapiro, "Online dictionary learning for sparse coding," ICML '09: *Proceedings of the 26th Annual International Conference on Machine Learning* (2009).
26. X. Zhang, J. Saniie, A. Heifetz, "Neural learning based blind source separation for detection of material defects in pulsed thermography images," *IEEE International Conference on Electro-Information Conference (EIT)* (2020).
27. X. Zhang, T. Gonnot, J. Saniie, "Real-time face detection and recognition in complex background," *Journal of Signal and Information Processing* 8, 99-112 (2017).
28. N Rajic, "Principal component thermography for flaw contrast enhancement and flaw depth characterisation in composite structure," *Composite Structures*, 58(4), 521-528. (2002).
29. X. Zhang, W.J. Yi, J. Saniie, "Home surveillance system using computer vision and convolutional neural network," *Proceedings of 2019 IEEE International Conference on Electro Information Technology (EIT)*, 266-270 (2019).
30. M. Aharon, M. Elad, A. Bruckstein, "K-SVD: An algorithm for designing overcomplete dictionaries for sparse representation," *IEEE Transactions on Signal Processing* 54(11), 4311-4322 (2006).

31. T. T. Cai, L. Wang, “Orthogonal matching pursuit for sparse signal recovery with noise,” *IEEE Transactions on Information Theory*, 57(7), 4680-4688 (2011).
32. D. Carpenter, G. Kohse, L.-W. Hu, *MITR User’s Guide*, Rev. 3 (2012).

Nuclear Science and Engineering (NSE) Division

Argonne National Laboratory

9700 South Cass Avenue, Bldg. 208

Argonne, IL 60439

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