Project title:	Image-guided Additive Manufacturing
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Industry collaborators:	CIMP-3D
Thrust area:	Intelligence
Current TRL:	TRL-4
Final TRL:	TRL-8
Project type:	Proposed project
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Completion date:	09/30/2017
Percent complete:	30%
Budget:	$50,000
IAB funding:	$0
Other funding:	$0

Industrial Relevance

Despite the rapid growth of market, additive manufacturing (AM) has experienced a **high rejection rate** (>2%) and **long post-build inspection** (~25% of the manufacturing time). In this study, an ***in-situ image sensing, fusion and decision-support system*** is proposed for ***real-time defect mitigation*** in AM. The proposed system extracts useful information from imaging data for layer-by-layer quality assessment, which will improve the build quality, reduce costs and increase the yield of AM.

Problem Statement

Motivation: Recent years have witenessed an rapid market growth of additive manufacturing. In 2015, the market of additive manufacturing industry was $4 billion. This value is estimated to reach over $10 billion by 2021. However, additive manufacturing is limited in its ability to perform real-time quality control, which poses a great challenge for mass use and widespread applications. For example, microstructure and mechanical properties of additive manufacturing builds will be significantly perturbed by process variations and uncertain factors (e.g., laser or galvo instabilities or drift, thermal effects, variations in powder feedstock). This, in turn, causes inherent defects (see Fig. 1) and impacts the build's strength and hardness. As a result, ***the rejection rate*** of additive manufactured parts is high (>2%). **Gap:** Current practices conduct post-build inspection or destructive tests for quality control of additive manufacturing products. ***Long inspection procedure*** (~20% of the manufacturing time for inspecting the engine part) results in a low yield and a high cost. Modern industries are investing in advanced sensing technology to cope with system complexity and increase information visibility. Sensing advancement brings large amounts of ***high-dimensional images***, which are critical to quality inspection and process improvement. However, very little has been done to develop enabling tools that will handle large amount of imaging data and extract pertinent information about process dynamics. The **reserach objective** of this project is to fill the gap by developing an in-situ image sensing, fusion and decision-support system for real-time defect mitigation in additive manufacturing.

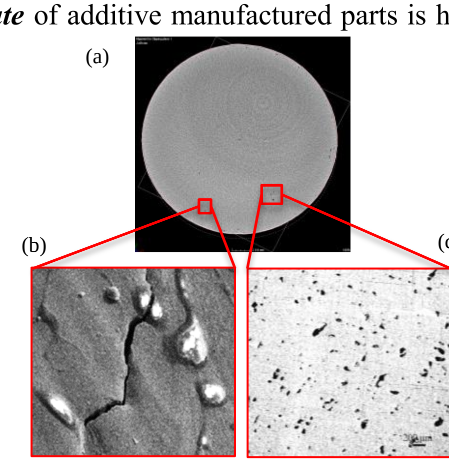

Fig. 1. Defects in additive manufacturing; (a) CT scan of one layer; (b) micro-cracks; (c) porosity.

Approach and Method

In this project, we propose to design and develop an ***in-situ image-guided monitoring and control system*** for additive manufacturing. As shown in Fig. 2, we will first build an ***in-situ image sensing system***, which captures in-situ images and CT scans of each layer of the part during the process of 3D printing. Second, we propose to represent each image as a network. As such, a ***dynamic network*** is obtained from the stream of time-varying images. Third, we will introduce a new approach of ***Potts model Hamiltonian*** to characterize ***community structures*** of dynamic network. When the Hamiltonian function is minimized, strongly connected network nodes are clustered into the same community. Fourth, we propose a new control chart, namely ***network generalized likelihood ratio chart (NGLR)***, to detect the change point of the underlying dynamics in complex additive manufacturing processes. Finally, a ***close-loop control policy*** will be established for ***real-time defect mitigation***.

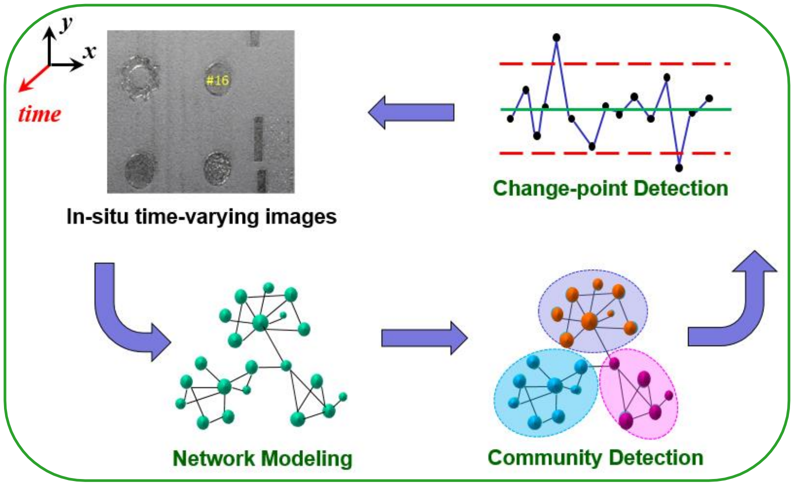

Fig. 2. Flow chart of the proposed research methodology.

Deliverables and Benefits

Towards the end of the project, we will have deliverable items in both hardware and software. We will build ***an in-situ image sensing system*** that will capture in-situ images and CT scans of a single layer of the product during the process of 3D printing. Industry practitioners will be able to directly use our developed system in manufacturing practices to capture in-situ high-dimensional images of additive manufacturing products. In addition, we will develop ***a software package*** that extracts useful features from images for the real-time detection and mitigation of defects. The software package will come with a ***user-friendly graphical interface***, which can be installed into the computer that is connected with the image sensing system. Manuals and guidelines of the system will also be provided.

Potential Application Areas

In general, the proposed system has strong potential to be applied to diverse industries with in-situ imaging data. The application areas includes (but not limited to) medical research, nano-manufacturing, semi-conductor manufacturing, food industry and bio-manufacturing.

Project Plan and Progress

The project plan includes 1) review current literature, data cleaning and pre-processing; 2) extract features from image data to characterize process; 3) develop data-driven models to derive quantitative relationships between image features and defect evolutions; 4) develop image-guided control policy of additive manufacturing and 5) evaluation and validation. The Gantt Chart is shown as follows,

	Month 1-2	Month 3-4	Month 5-6	Month 7-8	Month 9-10	Month 11-12	End
Literature review							
Data cleaning							
System development							
o Image feature extraction							
o Data-driven models							
o Image-guided control							
Evaluation and validation							
Document and presentation							

Current State of Practice and Research

Existing process control methods and tools focus on key product characteristics, linear and nonlinear profiles, as opposed to large amounts of image profiles that are nonlinear and nonstationary. In the past few years, in-situ image data have attracted increasing interests. For example, Du *et al*. analyzed hyperspectral images of poultry carcasses. A spectral band selection approach was developed to extract features for the detection of skin tumors. Megahed *et al*. compared the manufactured tiles with a specific pattern and designed a generalized likelihood ratio chart to detect the non-conforming tiles. Park *et al*. investigated microscopic images of nanoparticle dynamics. Morphology of nanoparticles were characterized by a multistage procedure and then semi-automatically classify them into homogeneous groups. Yan *et al*. proposed to integrate low-rank tensor decomposition with multivariate control charts for image-based process monitoring. In addition, Zhang *et al*. measured the variations of wafer thickness from image profiles using an adaptive Gaussian process model.

Gap: *However, most previous studies focus on fault detection from snap-shot images. Very little work has been done to characterize and model process dynamic images that are highly nonlinear and nonstationary in the additive manufacturing process.*

How Ours is Different

The proposed image-guided additive manufacturing is the first of its kind, which will help address defects, improve build quality and increase yield. Specifically, our contributions are as follows:

1) We propose ***in-situ process monitoring and control*** (*rather than traditional post-build inspection*), which eables real-time in-process defect detection and mitigation.
2) The proposed research provides an enabling tool to handle ***high-dimensional images*** (*rather than low-dimensional quality variables*) and extract pertinent knowledge about process dynamics for optimal control of additive manufacturing.
3) The proposed research addresses the complex structure of ***dynamic image streams*** (*rather than traditional static snap-shot images*) for in-situ monitoring and control of nonlinear and nonstationary process in additive manufacturing.