Data Driven Modeling, Statistical Analysis, and Machine Learning for Additive Manufacturing

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Abstract

In metal additive manufacturing (AM), materials and components are concurrently made in a single process as layers of metal are fabricated on top of each other in the (near) final topology required for the end-use product. Consequently, a large number of processing degrees of freedom (tens to hundreds) must be simultaneously controlled and understood; hence, metal AM is a highly interdisciplinary technology that requires synchronized consideration of physics, chemistry, materials science, physical metallurgy, computer science, electrical engineering, and mechanical engineering. The use of modern statistics-based approaches to modeling data sets with many degrees of freedom (known as machine learning) with metal AM can reduce the time and cost to elucidate and optimize the complex multidisciplinary phenomena. Machine learning techniques have been used in materials science for several decades. Most prolifically, the density functional theory community (DFT) rapidly adopted machine learning and has used it since the early 2000s for evaluating many combinations of elements and crystal structures to discover new materials. This focused review examines the potential of machine learning in metal AM, highlighting the many parallels to previous efforts in materials science and manufacturing, and discusses new challenges specific to metal AM.

1. *In Situ Process Monitoring and Feedback*

Computer vision is a class of image recognition algorithms that have been developed for automated feature identification in images. Intelligent computer vision utilizes machine learning algorithms to identify objects and features in images and time-series data.

Computer vision can be employed in additive manufacturing to monitor the printing process, such as measuring temperature profiles, observing melt pool morphologies, and automatically detecting defect formation. Doing so will require methods for in situ process monitoring and data collection. Thus far, in situ control in AM has been consistently ranked as one of the most-needed technologies for advancing the technology [1–3]. The combination of rapid solidification and the small length scales of AM solidification can make traditional process monitoring approaches difficult. Machine learning can fill in gaps where human-specified process monitoring models are insufficient.

Process monitoring involves acquisition of realtime signals which can be processes to reveal information about manufacturing. McKeown et al. used dynamic transmission electron microscopy to measure solidification rates in powder bed AM [4]. Bertoli et al. also characterized cooling rates using high speed imaging [5]. Raplee et al. used thermography to monitor the solidification and cooling rates of electron beam powder bed fusion, then related the temperature profiles to defect and microstructural characteristics [6]. Distortion of parts due to thermal cycling was investigated by Denlinger et al. by means of thermocouples in contact with the build substrate [7]. All of these methods are amenable to aid by computer vision.

There are two areas of need for in situ measurement:

- Processing of signals real time to identify features of the AM process
- Multi objective feedback and control

There are several review articles on AM (Tapia, for example) which could go here, or could go in the intro paragraph of Section III.c

Many of the difficulties in real time signal processing is the complexity and number of signals being acquired. Identifying features of interest in a signal becomes difficult when the necessary signal features to identify are not known. Researchers are well aware that defects form during the additive process. Which signals to monitor and what about the signals are indicative of a defect is not known.

Setup for the following information:

- Explain the concept of identifying features in images (filters, SIFT/SURF)
- Explain template matching using a dictionary of identified features
- Explain the concept of 'learning' filters through a CNN
- Explain the use of CNNs in AM process monitoring
- Move Gobert to case study section

Convolutional neural networks (CNNs) have proven to be one of the best computer vision approaches for identifying complex features in images **citation?**. At the highest level, CNNs use large databases of labeled information to learn features in the image that indicate whether or not certain human-identified objects are present. The level of abstractness of the object is arbitrary, so long as the dataset contains enough images with each feature to be identified. This is an improvement over current methods whereby humans develop models specifically to identify features of the printing process. Human-specified models for defect detection – **search around the literature you've cited for an example of a human-specified model that is very specific to the problem being address, perhaps Abdelrahman? [8].** – can be limited in their ability to identify edge cases, as well as in their ability to detect multiple types of defect formation. Convolutional neural networks can identify multiple features or defects in an image simultaneously. A downside to CNNs is that they require **very** large datasets (thousands of images, at the least) of labeled data to be successful. Neural networks have already been implemented for in situ AM analysis by Scime et al. [9], Yuan et al [10].

Another computer vision approach is called *template matching* and does not require the same dataset size as CNNs. Template matching is the process of comparing computer-vision identified 'keys' in an image with a database of keys associated with a certain feature. For example, powder inclusion in a melt pool can often be characterized by a local change in reflectivity in the melt pool near the particle **cite???? where are you coming up with this, or are you asssuming?**. A feature identification algorithm such as the scale invariant feature transform (SIFT) [11] or speeded-up robust features (SURF) [12] can identify common characteristics of a powder inclusion in an image. Template matching involves using an algorithm like SIFT and SURF to identify features in an image, then compare those features with a database of typical AM features, like porosity or powder inclusion. If keys of the feature in the image closely match a key in the template database then it is likely that feature exists in the image.

I. HOW EXISTING ML APPROACHES CAN BE USED IN AM

A. The History of Machine Learning in the Material Sciences

B. Case Studies of Machine Learning for Additive Manufacturing

1. In Situ Monitoring

A study by Gobert et al. investigated using X-ray CT data to correlate with images obtained by a DSLR camera during the printing process. Gobert et al. printed a single part, containing several different features, and recorded the print results before and after every layer using a DSLR and eight different lighting conditions. The part was then characterized using X-ray CT to find the location and size of pores and inclusions. A regression model was trained between the location of the pores in the final part and the low resolution image data obtained during the build.

One of the underlying assumptions of the study was that, even though the DSLR images did not record during the melting and solidification process, features would appear in each image that could be correlated back to the higher-resolution data in the CT images. The use of a regression model also meant that future images could be analyzed to predict whether or not pores had formed in various locations. The study by Gobert et al. was able to accurately predict whether or not an image contained a defect with 85% accuracy after all the DSLR lighting conditions were combined into an ensemble classifier.

With this type of in situ image recognition, defect formation can be detected during the printing process, precluding the need for certain post-characterization techniques. If defects form and are detected, then the printing process can be stopped, saving powder/feedstock, operating costs, and operating time. However, an even more desirable result is to first detect defect formation, then correct for it in situ. To do so, information will have to be assembled that relates the detection of defects, the manner in which the defects formed, and the prescribed fix to undo or stop the defects from growing. It is likely that combining all these information sources will require a significant leap in scientists' ability to apply machine learning algorithms to widely varying data sets and types.

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