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Prediction of porosity in metal-based additive manufacturing using spatial Gaussian process models

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ABSTRACT

Additive manufacturing (AM) is a set of emerging technologies that can produce physical objects with complex geometrical shapes directly from a digital model. With many unique capabilities, such as design freedom, it has recently gained increasing attention from researchers, practitioners, and public media. However, achieving the full potential of AM is hampered by many challenges, including the lack of predictive models that correlate processing parameters with the properties of the processed part. We develop a Gaussian process-based predictive model for the learning and prediction of the porosity in metallic parts produced using selective laser melting (SLM – a laser-based AM process). More specifically, a spatial Gaussian process regression model is first developed to model part porosity as a function of SLM process parameters. Next, a Bayesian inference framework is used to estimate the statistical model parameters, and the porosity of the part at any given setting is predicted using the Kriging method. A case study is conducted to validate this predictive framework through predicting the porosity of 17-4 PH stainless steel manufacturing on a ProX 100 selective laser melting system.

1. Introduction

Additive manufacturing (AM) has recently gained increased attention by researchers, practitioners, and even public media [1–3]. It is regarded by some as a potential game changer, especially with the advent of AM technologies that can process advanced metallic materials and alloys such as stainless steel [4–6], Ti-6Al-4V [7,8], and nickel-based alloys [9]. In contrast to the limited application of polymer-based AM in producing visualization or functional prototypes to accelerate product development in the early 1980s, metal-based AM is now used to produce parts for direct use such as the fuel nozzle that GE Aviation will use in their LEAP engine [10,11], Lockheed's blead air leak detector [12], and biomedical cranial and hip implants [13–15].

There are many obstacles that still hamper the widespread adoption of metal-based AM as a mainstream manufacturing method. These include for example part quality, repeatability, and the lack of material and process standards, among others. Many recent road mapping efforts have been conducted by academic and industrial stakeholders to identify technological barriers, desired capabilities, and research efforts needed to unlock the opportunities that AM has to offer (see for example the roadmap for additive manufacturing [16] and NIST's measurement science roadmap for metal-based additive manufacturing [17]). These efforts have been instrumental in providing guidance and vision for researchers, and their impact on the advancement of AM technologies is starting to be realized [18].

One of the missing and highly desired capabilities, aligned both with the vision of these road mapping efforts as well as industrial needs, is providing modeling and simulation capabilities that decrease the need for real-world testing and provides designers with predictive capabilities to optimize part and process design [17, p. 35]. This is important due to the high costs associated with experiments and testing needed to achieve the desired part properties. It is further complicated by the fact that most metal-based AM technologies involve many process parameters and complex physical transformations that influence the properties of the final part.

In this work, we develop a predictive modeling framework based on Gaussian process (GP) models to predict the resulting density (or porosity) in parts manufactured using selective laser melting (SLM) as a function of the processing parameters. SLM is a laser-based metal AM process that produces physical parts directly from a computer digital model, layer upon layer, by selective fusing metallic powder using a high energy laser beam [19]. Porosity is a common

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defect that has been reported in SLM parts, resulting in compromising the mechanical properties and performance of the part. It is well established that excessive concentration of pores in the part's structure could reduce tensile strength, ductility and fatigue properties [20]. Multiple mechanisms contribute to porosity in SLM parts. These include shrinkage, gas entrapment during solidification [21,22], and adhesion of partially molten particles to surfaces between layers [23]. Additionally, depending on the wettability, capillary forces and surface tension of the melt pool, a defect known as "balling" can occur which results in uneven subsequent powder layers and, consequently, pores upon processing of the material [24].

Selection of multiple processing parameters such as laser power, scanning speed, and layer thickness [25] impact part porosity. The majority of existing efforts rely on extensive round-robin testing for selecting parameter combinations that maximize part density and minimize porosity. In contrast, we develop a systematic approach that enables accurate prediction of porosity at any given parameter combination while keeping the number of costly experiments to a minimum. In particular, we develop a GP regression model to express part porosity as a flexible stochastic function of SLM processing parameters, and use a Bayesian inference procedure to estimate the model parameters and subsequently predict porosity.

Gaussian process models have been widely used in Bayesian nonparametric statistics to specify prior distributions on function spaces due to their desirable mathematical and computational properties, and ability to incorporate a wide range of smoothness assumptions [26]. Examples include spatial modeling [27], computer model emulation [28,29], image analysis [30], and supervised classification and prediction in machine learning [31]. The popularity of such processes are mainly due to their many attractive mathematical and computational properties, and their flexibility and richness in modeling dependence among data observed in space. Our work is among the first to introduce spatial GP models to addressing the modeling and prediction of metal-based AM processes. We validate our methodology using real-world data that we acquired from building 17-4 PH stainless steel test coupons using SLM.

The paper is organized as follows: Section 2 surveys relevant literature related to metal-based AM and statistics, with emphasis on works that studied the manufacturing of 17-4 PH stainless steel. In Section 3, we define the problem and formulate a GP regression model for predicting porosity in metallic parts produced using SLM. We then present a Bayesian inference method for estimating the parameters of this model, and use these estimated model parameters for prediction in Sections 4 and 5, respectively. A real-world case study is conducted in Section 6 to validate the proposed predictive framework using data from the production of 17-4 PH stainless steel samples on a commercial SLM system housed in the authors' laboratory. Finally, concluding remarks and directions for future research are outlined in Section 7.

2. Literature review

Additive manufacturing (AM) technologies are currently categorized into 7 distinct categories according to the material being used and the mechanism with which each layer is produced [32]. The two most common process categories used for producing metallic parts are powder bed fusion (PBF) and directed energy deposition (DED) processes. This is primarily due to their ability of producing dense metallic parts without the need for significant post processing [19]. Both categories share the common aspect that parts are produced by melting metallic powder using an high energy source (commonly a laser or electron beam). The key difference between them is the powder feed mechanism: in PBF, the energy source melts powder placed in a powder bed, whereas in DED the powder is coaxially fed with the energy source. Our focus in this work is on selective laser melting (SLM) which is a class of PBF processes that fuses metallic powder using a laser beam. Excellent overviews and summaries of different AM process categories and technologies are provided by Wohlers [10] and Gibson et al. [23].

The body of the literature on SLM is quite large, studying the fabrication of different metallic materials such titanium alloys [7,33,34], aluminum alloys [35–37], and nickel alloys [38,9,39]. We consider the SLM of steel in this study, which has been frequently studied. Some of the investigated steel alloys include austenitic 316L stainless steel [40,6,41,42], H13 tool steel [43,44], and maraging steel [45,46]. Our choice of precipitation hardening martensitic steel (17-4 PH) for this study has two main motivations: first, this alloy has wide used in industrial applications that require a combination of high strength and a moderate level of corrosion resistance [47,48]; and second, it is commercially available in gas atomized powder form for SLM applications.

Most of the works on the SLM of 17-4 PH steel investigate its manufacturability and analyze the properties of the fabricated parts. For example, Facchini et al. [49] analyze the microstructure and Kumar and Kruth [50] study the wear behavior of SLM-fabricated 17-4 steel parts. Murr et al. [51] provide a good review on efforts in processing 17-4 PH steel and other metallic alloys using laser- and electron beam-based AM, with a focus on reporting the microstructure and phase structures.

Very few works follow systematic approaches for assessing the impact of SLM process parameters on the properties of the end part. One example is the work by Averyanova et al. [4] who use a fractional factorial approach to assess the impact of process and material parameters on the dimensional stability and surface roughness of a single layer 17-4 PH. The effect of the optimized process parameters on the microstructure of the final part is subsequently studied in [52]. Spierings et al. [53] employ full-factorial experimental design examine the effect of energy density on the density and elasticity of 17-4 PH specimens. Gu et al. [54] and Averyanova and Bertrand [55] also study the effect of process parameters on the density of 17-4 PH specimens, however the values of process parameters were arbitrarily selected.

In contrast to the above works, we construct a predictive model that provides a systematic framework for predicting the porosity (or density) of SLM-fabricated 17-4 PH steel motivated from Gaussian process models widely used in spatial statistics.

Spatial statistics started as an ad-hoc field with few works dated as back as the early 1900s, however strong theoretical research has been developed since the 1950s, with applications focused on mining, agriculture and forestry [56]. It experienced significant growth over the past two decades particularly with the development of low-cost high-speed computing [56,57], extending its application domains into other fields such as healthcare, social and environmental geography, oil and gas exploration, fisheries and animal migration, socioeconomics and econometrics, among others [58]. To date, fewer works use spatial models in manufacturing applications. Yang and Jackman [59] scan points on the surface of a workpiece and use a spatial model to predict and estimate form (geometry) errors. Colosimo et al. [60] propose a process control method that combines control charts with spatial correlated noise, and apply this method to monitor the roundness geometrical tolerance for parts produced by turning. A similar hybrid approach encompassing spatial information with control charts is used by Collica et al. [61] for quality control in the manufacturing of integrated circuits. Hsu and Chien [62] develop a data mining approach that integrates spatial statistics with adaptive neural networks to identify patterns of defects in semiconductor manufacturing. The authors use a case study to demonstrate their approach can be used to provide information on production defects and their root-causes.