G Model
CIRP-1852; No. of Pages 4

ARTICLE IN PRESS

CIRP Annals - Manufacturing Technology xxx (2018) xxx–xxx

Contents lists available at ScienceDirect

CIRP Annals - Manufacturing Technology

journal homepage: http://ees.elsevier.com/cirp/default.asp

Machine learning in tolerancing for additive manufacturing

Zuowei Zhu [a], Nabil Anwer (2)[a,*], Qiang Huang [b], Luc Mathieu (1)[a]

[a] LURPA, ENS Cachan, University Paris-Sud, Universite Paris-Saclay, 94235 Cachan, France
[b] Daniel J. Epstein Department of Industrial and Systems Engineering, University of Southern California, Los Angeles, CA 90089, USA

ARTICLE INFO

Keywords:
Tolerancing
Additive manufacturing
Machine learning

ABSTRACT

Design for additive manufacturing has gained extensive research attention in recent years, whereas tolerancing issues aiming at controlling geometric variations remain a major bottleneck in achieving predictive models and realistic simulations. In this paper, a prescriptive deviation modelling method coupled with machine learning techniques is proposed to address the modelling of shape deviations in additive manufacturing. The in-plane geometric deviations are mapped into an established deviation space and Bayesian inference is used to estimate geometric deviations patterns by statistical learning from multiple shapes data. The effectiveness of the proposed approach is demonstrated and discussed through illustrative case studies.

1. Introduction

Additive manufacturing (AM) has gained extensive industrial and research attention in recent years. The layer-wise characteristic of AM conveniently enables the manufacturing of products with complex shapes and various materials. Design for additive manufacturing (DfAM) is currently receiving much research attention and has spawned interest in the development and validation of design guidelines, methodologies and tools to assess the consistency between the digital and physical product in AM [1].

As a key issue to product design, tolerancing aims to control the geometric deviations of the final product with respect to manufacturing and functionality requirements. However, complex error generation mechanisms underlying AM digital and physical chains are likely to result in geometrical inaccuracies of the final product, thus posing significant challenges to design and tolerancing for AM [2]. Therefore, predictive modelling of shape deviations is critical to tolerancing for AM [3].

Unlike other manufacturing processes, AM defects' analysis and modelling is not mature yet. The research field is still in its infancy, but it benefits from the maturing age of data mining and analytics and machine learning techniques and their successful applications in many engineering domains.

With increasing volumes and varieties of data, machine learning has gained extraordinary popularity due to its ability to explore complex patterns in observed data and make data-driven predictions or decisions on new data. Many machine learning techniques and algorithms have been reported in the literature. Among them transfer learning and multi-task learning [4] are suited for reusing previously acquired data contained in multiple related tasks to solve new but similar problems more effectively.

Motivated by the potential advantages offered by machine learning in tolerancing for AM, this research aims to develop new shape deviation models based on machine learning techniques.

In this paper, a new model is proposed combining a transformation perspective [5] to model the systematic shape-independent deviation and a multi-task Gaussian process method to model the shape-dependent deviation by simultaneously learning from the deviation data of multiple shapes.

2. Shape deviation modelling in AM

AM geometric deviation modelling has been investigated for various AM processes from multiple aspects, including characterization of geometric approximation errors during conversion from CAD model to standard input files, parametric modelling of machine errors and identification of influential process factors on shape shrinkage ratio. The focus of these methods is concentrated on a global improvement of geometrical accuracy.

In order to derive more specific models of shape deviation, Huang et al. intuitively decompose AM shape deviation into in-plane and out-of-plane deviation, and have developed deviation models incorporating only the shape parameters based on statistical methods [6].

The rapid development of measurement technologies and machine learning techniques provides the possibility to obtain efficient deviation models from large amounts of manufactured data. The Gaussian process method has been adopted in form error assessment to reconstruct part surface and estimate an empirical distribution of the form error based on a number of measured points [7]. Multi-task learning algorithms are used in machined surface prediction by transferring the knowledge between

* Corresponding author.
E-mail address: anwer@lurpa.ens-cachan.fr (N. Anwer).

https://doi.org/10.1016/j.cirp.2018.04.119
0007-8506/© 2018 Published by Elsevier Ltd on behalf of CIRP.

multiple similar-but-not-identical processes [8]. Especially in AM deviation modelling, an artificial neural network algorithm has been proposed to learn from thermo-mechanical deformation data gathered from finite element simulation [9]. A Gaussian process model is proposed by Cheng et al. to capture the effect of nominal shape and process parameters on in-plane shape deviation, and further they propose a transfer learning perspective to model shape-specific deviation across multiple shapes [10].

However, the performance of these methods is closely associated with the studied shape. The complexity of product geometry and AM processes also affects the generalization of reported models and new parameters have to be introduced and estimated for new shapes and processes. Moreover, the highly nonlinear relationships between error sources and shape deviation can hardly be modelled using simple empirical functions derived from a set of samples.

3. Transformation perspective for AM deviation modelling

The error generation mechanism in an AM process can be explained regarding three main error sources: the mathematical geometry approximation error due to conversion from CAD model to the standard file input; the process-induced error resulting from machine errors and process characteristics; and the material-related error such as thermal shrinkage and material distortion arising from the rapid heating and cooling process [11]. Due to the layer-wise nature of AM processes, the effect of error sources is reflected both inside each layer and between layers, thus resulting in in-plane and out-of-plane deviations of the product shape from its nominal design [6]. In this paper, we focus on the in-plane case. The small layer thickness allows us to reduce this problem as a two-dimensional (2D) problem by approximating the boundary of a layer with a 2D shape. Quantification of the variational effects on the designed 2D shape is essential to the effective modelling of AM shape deviation, thus motivating us to investigate the transformations of the designed shape as a result of the complex error sources.

The transformation perspective can be reasonably justified based on the fact that, the process-induced error, such as undesired displacement of machine axes or energy sources, may cause slight translation and rotation of shape with respect to the machine coordinate system, and the material-related error, such as thermal shrinkage, may cause local variations of shape from its nominal form. The stack-up of layers will accumulate these deviations and as a result affect the overall product form. Therefore, three kinds of transformations can be defined on a 2D shape in the x–y building plane: translations in x- and y-direction Δx, Δy, rotation with respect to the origin α and scaling in x- and y-direction φx, φy. Fig. 1 illustrates the transformation effects on the designed shape during the AM process.

A mathematical relationship between the designed shape Ω° and the final shape Ω^{*} can be established based on the transformation parameter set $\Psi = \{\varphi x, \varphi y, \alpha, \Delta x, \Delta y\}$. Suppose corresponding points on Ω° and Ω^{*} are denoted as (x°, y°) and (x^{*}, y^{*}) in the Cartesian coordinate system (CCS), this relationship

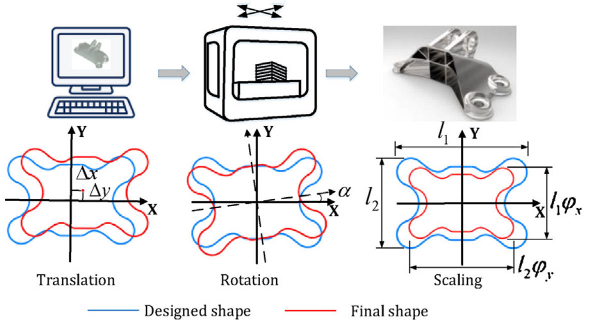

Fig. 1. Variation of 2D product shape in an AM process.

is defined as Eq. (1), in which M^S, M^R, M^T are homogeneous transformation matrices composed of scaling, rotation and translation parameters respectively.

$$(x^{*}, y^{*}, 1)^T = M^S M^R M^T (x^{\circ}, y^{\circ}, 1)^T \quad (1)$$

Resolving Eq. (1) yields:

$$(x^{\circ}, y^{\circ}) = (h_1(x^{*}, y^{*}, \Psi), h_2(x^{*}, y^{*}, \Psi)) \quad (2)$$

In order to facilitate the modelling of in-plane deviation, the polar coordinate system (PCS) is adopted due to its ability to analytically represent common planar shapes, with a single function if its origin is inside the shape boundary. The in-plane deviation function is then defined as the difference between the radii of the final shape and the designed shape at corresponding locations $\theta \in [0, 2\pi)$ along the 2D shape boundary, as shown in Eq. (3).

$$f(\theta; \Psi) = r^{*}(\theta; \Psi, r^{\circ}(\theta)) - r^{\circ}(\theta) \quad (3)$$

For a shape that has explicit function $c(x^{\circ}, y^{\circ})$ in CCS, the analytical formulation of both $r^{\circ}(\theta)$ and $r^{*}(\theta; \Psi, r^{\circ}(\theta))$ is conveniently achieved combining Eq. (2).

In a more general case, an arbitrary convex polygonal shape for instance, $f(\theta; \Psi)$ could be derived in an edge-wise manner. As illustrated in Fig. 2(a), the polar radius of a polygonal shape at θ is calculated regarding the specific edge (defined by two neighbouring corner points $P_a(x_a, y_a)$ and $P_b(x_b, y_b)$) that intersects with the ray of θ. Following this principle, $r^{\circ}(\theta)$ and $r^{*}(\theta; \Psi, r^{\circ}(\theta))$ could be evaluated at any given θ. For more complex shapes, e.g., shapes with internal holes or concave shapes on which more than one point may exist for a given angle in PCS, multiple PCSs have to be built to collectively model the boundary of holes or concave segments.

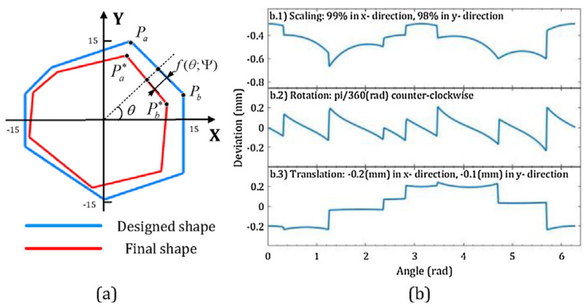

Fig. 2. (a) Shape deviation of a polygonal shape (b) deviation patterns in the deviation space.

Eq. (3) provides parametric modelling of the in-plane shape deviation as a function of the polar angle. The deviation modelling problem is now mapped into a new space composed of the polar angle and in-plane deviation, which we call the deviation space. The transformation perspective enables the direct investigation of systematic deviation patterns in the deviation space, and is independent from the specific shape. Fig. 2(b) illustrates three deviation patterns of the polygonal shape in Fig. 2(a) resulting from different transformation effects. These patterns are generated by separately setting the parameters in Eq. (3) as $\varphi x = 0.99$, $\varphi y = 0.98$ (Fig. 2(b.1)), $\alpha = \pi/360$(rad) (Fig. 2(b.2)) and $\Delta x = -0.2$(mm), $\Delta y = -0.1$(mm) (Fig. 2(b.3)).

4. Predictive deviation modelling using machine learning

Since the transformation parameters in Eq. (3) are applied to the overall shape, the parametric function is able to capture the global trend of in-plane shape deviation. However, there exist unexplained variations along the shape boundary that are location-dependent and exhibit far more complex patterns. These patterns might be associated with the specific shape and are beyond the