Feature Characterisation of additively manufactured Implants made of Ti6Al4V using Hybrid Machine Learning Models, Measuring Data, and Process Parameters

Sahar AL-Zaidawi ^{1,2}, Anastasiya Tönjes ², Stefan Bosse ^{1*}

In the case of medical products, in particular implants, high demands are placed on the materials and their properties. With additively manufactured implants made of Ti6Al4V, porosity develops due to the process. In terms of process technology, this is kept to a level of less than one percent and is often almost completely closed by a connected thermomechanical after treatment, HIP for short (hot isostatic pressing). Thus, the end products have almost no recognizable porosity anymore.

Nevertheless, there may be significant differences in the mechanical properties. In this case, especially with the dynamic loading of the components. Since a failure of implants causes a highly sensitive situation, the relationship between the process parameters in the manufacturing process and the mechanical properties must be investigated. Of particular interest is the influence of the final properties by the HIP.

The very high cooling rates in the PBF-LB / M process (Powder Bed Fusion with Laser Beam of Metals) of up to 107 K / s result in such a fine microstructure that differences and individual phase components are difficult to identify. The present alloy (Ti6Al4V) is an alphabeta titanium alloy. Due to the PBF-LB / M process, the phase components can be shifted to a moderate extent in favor of alpha or beta. The alpha phase shows high strengths with low elongation at break and the beta phase, on the contrary, shows lower strength with higher elongation at break. If necessary, a burn-off of the alloying elements can be provoked by a high energy introduced in the build-up process, which can also result in a shift of the phase components (for example, burn-off of alpha stabilizer aluminum). The mechanical properties prevailing after the assembly process can be greatly adapted or even completely rotated by the HIP. This raises the question of the interrelationships between the process parameters and the resulting mechanical properties across the process steps.

Using models of machine learning and image analysis, differences in the microstructure such as

- Melt trace size and shape,
- · Grain size,
- Phase components, alpha and Beta
- Phase characteristics (shape, size and position),
- Grain and phase orientation, as well as
- Pores [1]

can be recognized, described and associated with the process parameters and mechanical properties. Here, samples in the as-built as well as in the hyped state are to be examined. Challenges exist in particular in the differentiation and identification of features in the very fine microstructure as well as the relatively small number of laboratory tests due to the experimental and preparation effort.

¹ University of Bremen, Dept. of Mathematics and Computer Science ²Leibniz IWT, Bremen, Germany *sbosse@uni-bremen.de

An experimental design will be developed in cooperation between the data sciences and the materials sciences, which should lead to a continuous refinement of the models through an iterative procedure.

Proposed data science and analysis methods and algorithms:

- Density-based clustering
- CNN / Region-based CNN, F-RSN
- Residual Neural Network
- Autoencoder-based anomaly detectors
- Numerical approaches, image transformations, clustering analysis

Formally, there is a model predictor function $f(x):x \to y$, with input x as measuring data from a set of experiments and specimens, and output y characterizing features of the manufactured material. The target features have relevant impact on the lifecycle and robustness of medical implants, which have to be identified, too. The input data is heterogeneous, but often it consists of images, therefore image analysis and object detection (with ROI) are fundamental pre-processing steps [2]. There is a large set of already available object detectors, e.g., coco-ssd. A major challenge in object detection is the complexity of ROi proposals with respect to model complexity and computational complexity. Using pure data-driven models, e.g., coco-ssd, trained for environmental scene recognition, the ROI proposal and object detection in measuring images, e.g., from pore micrographs, will result in bad coverage and accuracy. For this reason, we will apply model-assisted object detectors, e.g., to find critical material pores, to identify cracks, and different material regions.

References

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