Joint Special Interest Group meeting between euspen and ASPE
Advancing Precision in Additive Manufacturing
Inspire AG, St. Gallen, Switzerland 2021
www.euspen.eu

Smart machines for fused filament fabrication based on multi-sensor data fusion, digital twins and machine learning

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Abstract
Among additive manufacturing technologies, fused filament fabrication (FFF) is becoming increasingly important for high-performance applications, e. g. in the biomedical and pharmaceutical fields, which require products to conform to strict functional and geometric specifications. At the state-of-the-art, in-process monitoring is being actively investigated to improve FFF: monitoring the machine and the part during the fabrication provides opportunities for keeping quality under constant control, allowing for early process termination or for taking corrective actions in case issues are detected.
In this work, ongoing research towards the implementation of a "smart" FFF machine is illustrated, where sensing and machine learning are combined to achieve real-time process monitoring and capability for self-adjustment. Through sensors, a smart FFF machine can monitor extrusion rate, temperatures and pressure. Machine vision can be used to monitor the geometry and topography of the current layer, detecting both topographic defects and part shape errors as they appear. A fundamental role is played by the presence of digital twins, i.e. computer simulations of the part being fabricated and of the FFF system, which are used by the machine AI as an aid to the decisional process, and are continuously updated through sensor data to reflect the current state of fabrication. The current opportunities and open challenges of developing a smart FFF machine are highlighted through the illustration of an open, modular architecture which we have been developing as a testbed for multisensing and AI in FFF. Issues are discussed through the application to a selected set of test cases.

Artificial intelligence, 3D printing, In-process measurement, Monitoring

1. Introduction

Fused Filament Fabrication (FFF) is an additive process in which objects are fabricated by extruding a thermoplastic material deposited in consecutive layers. Thanks to the development of innovative highly engineered materials [1,2] and to the freedom and flexibility allowed in part design, FFF is becoming increasingly appealing for high-performance applications, especially in the biomedical [3] and pharmaceutical [4] sectors and for the production of electric motor components [5] and embedded sensors [6]. High-performance applications require products to adhere to strict application-related design specifications, therefore FFF technologies are required to evolve to achieve higher part quality. To this effect, diverse in-process monitoring systems have been investigated as means to keep part and process quality indicators under control. Accelerometers have been used to detect nozzle clogging [7] and step losses [8]. Extrusion pressure and temperatures have been monitored using sensors embedded in the nozzle [9]. By means of infra-red thermal imaging, the extrusion temperatures and the processing condition of the layer have been observed [10], [11]. Acoustic emissions have been used to detect extruder failures [12] and other machine faulty states [13]. Layer imaging in the optical range has a fundamental role in process monitoring. Vision systems have been implemented to detect layer flaws [14], in some cases exploring the possibility to trigger corrective actions [15]. Optical imaging has also been used to observe the part from the side during the fabrication process [16] and to detect errors such as the detachment of the part from building platform and part deformation [17]. Finally, a system for extracting the outer boundary of each layer using layer images taken from above has been proposed [18].

In this work, we illustrate the ongoing development of a modular hardware-software framework to test new data analysis methods, machine learning and multisensor data fusion technologies applied to FFF. The system currently allows to monitor extrusion process parameters (extrusion pressure, material transport and temperatures), nozzle-part relative movement, and layer quality via optical imaging. Using imaging, the system is also able to reconstruct the evolving geometry of the part as it grows layer after layer. Finally, digital twins (DTs) of the extrusion process and of part geometry are maintained and used to aid in-process quality monitoring and defect detection.

2. The FFF hardware-software framework

The framework under development is based on the architecture of a commercial FFF machine [19] modified in order to accommodate heterogeneous sensing solutions and machine learning capabilities. The machine features a Cartesian architecture: the building plate moves along X and Y axes, while the extruder, mounted on a horizontal gantry, is moved along the vertical direction (Z).

The position of the extruder relative to the part under fabrication is monitored through three optical encoders (Broadcom-Avago AEDM-5810-Z12 [20]) installed on the axes X, Y, Z. Another two optical encoders are used to monitor filament transport and slippage events. Two shear beam load cells are

positioned above the hot end of the extruder, to measure extrusion pressure. The hot end is equipped also with four J-type thermocouples, three of which located in the nozzle, lodged in three blind holes machined with 30° tilt with respect to the extruder axis and angularly spaced by 120°. The fourth thermocouple is inserted in the heat block, in the same slot used for the system thermistor.

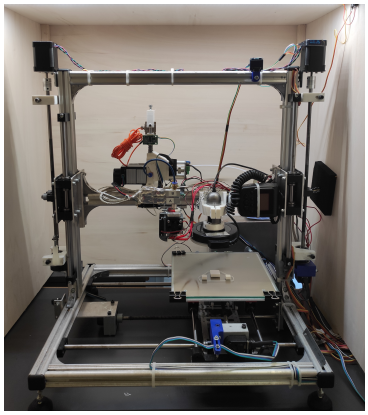

Figure 1. The FFF machine prototype inside the enclosure**.**

The sensor data streams are collected using a modular architecture based on National Instruments hardware [21]. The system is composed of a chassis Ni cDAQ 9185 on which four modules, dedicated to specific signal acquisition, are installed. The Ni cDAQ communicates with a PC, which manages the acquisition process through a Labview-based software, capable of reading and storing data provided by sensors while the machine is fabricating the part. An imaging system is mounted on the horizontal gantry, parallel to the extrusion system, and can host interchangeable cameras, to acquire top-down pictures of the part under fabrication. In Figure 1, the system is equipped with a digital video microscope (Dino-Lite Edge AM4515ZT 1.3 MP 20x~220x) and a ring-light source. The acquisition is triggered using one of the control board auxiliary digital ports which respond to specific command in the part fabrication program. Depending on the optics setup, the imaging system can be used to capture the entire layer in one shot or stitcheable sequences of higher-resolution regions, depending on monitoring target (small-scale defects vs part form errors). Also depending on the characterisation objectives, the FFF machine can be positioned inside a dedicated enclosure designed to cut out external light (Figure 1) and produce more uniform illumination conditions for imaging.

The machine control board is a Megatronics v3.2 [22], which features auxiliary digital ports useful to deliver custom command signals. These have been used to trigger the image acquisition, as mentioned above, and to generate a counter to tag the execution of g-code commands, so that sensor data can be mapped to the specific g-code command that triggered the execution of a specific portion of part program. The control board, equipped with Marlin firmware [23], is connected to a PC via serial interface and the communication is managed by the software Repetier-Host by Hot-World GmbH [24]. Data processing and analysis via machine learning are performed by a separate computer which receives the sensor data streams from the Ni cDAQ. By aggregation of heterogeneous sensor information, the monitoring system achieves a comprehensive view of the process and can detect issues that could not be reliably detected using a single sensor. The data streams are also routed to the associated digital twins (DTs), so that the simulation models can be updated in real time to support fabrication monitoring and the decisional process. In the following, to exemplify the capabilities of the framework, two subsystems are illustrated, one dedicated to monitoring process parameters during layer deposition and highlighting the potential of multi-sensor data fusion; the other dedicated to monitoring the outer contour of each layer and the growth of part geometry, highlighting the potential advantages of using digital twins to support data interpretation and process monitoring.

3. Monitoring the deposition process using multi-sensor data

Data recorded in-sync from positional encoders can be used to reconstruct the real extruder path followed during the entire fabrication process. The real path can be compared to the nominal one (calculated from automated analysis of the part program) in order to identify anomalies related to axis positioning errors. An example of this type of monitoring is reported in Figure 2 in relation to a test pyramid with base 20x20 mm and height 10 mm. The fabricated part (Figure 2a) is clearly defective due to an abrupt loss of positional reference happened roughly at mid-build. The issue is immediately detected through the analysis of multi-sensor data as illustrated in Figure 2b, where the real path as recorded by the encoders is plotted and coloured by deviation (local Euclidean distance) from the nominal path defined in the part program.

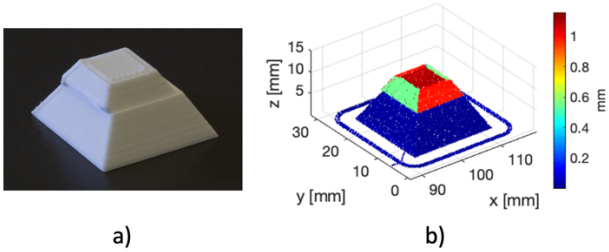

Figure 2. a) test pyramid with defective geometry due to axis reference loss; b) the anomaly is immediately visible via analysis of the encoder data and comparison with nominal expectations (part program).

As stated earlier, the framework is designed so that heterogeneous sensor data streams can be temporally and spatially co-localised. This allows for unprecedented freedom on the types of analyses which can be performed for process monitoring and optimisation. In Figure 3 extrusion paths related to individual layers are visualised, where coordinates have been extracted from the encoder data streams, whilst colouring is based on data from another two sensors, i.e. temperature at the extrusion nozzle (Figure 3a) and filament transport error due to slippage (Figure 3b). Both the maps refer to layers extracted from the pyramid shown in Figure 2. The data in Figure 3a shows how colder and hotter regions of the build can be detected, whilst Figure 3b allows to investigate for correlations between filament transport error and specific part regions. Similar plots using data from other sensors are illustrated in [25].

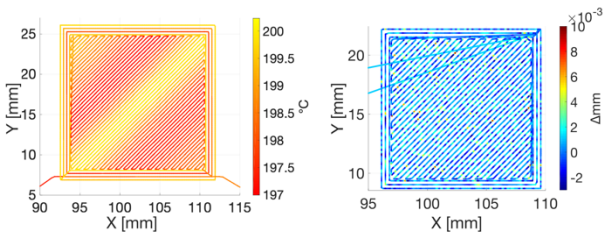

Figure 3. Layer extrusion path coloured by: a) local extrusion temperature; b) local filament slippage error.

4. Layer contour monitoring with machine vision and digital twins

The layer contour monitoring subsystem is based on the analysis of high-resolution images depicting portions of the layer contours. In this case, the microscope operates at ~8 mm from the surface, achieving a rectangular field of view of (9.34 × 7.48) mm, which, captured by a (1280 × 1024) pixel detector, results in a resolution of ~(7.3 × 7.3) µm/ pixel (data obtained after calibration). The calibrated pixel size is about one order of magnitude smaller than the preset deposited filament width of ~350 µm, thus allowing to detect irregularities in the shape and lay of the strand. An example image acquired with this method is depicted in Figure 4.

Images are acquired along each layer contour after the fabrication of the layer itself. The number and the position of the images is automatically determined with the help of a DT dedicated to estimating where the layer contours should be located at the current stage of fabrication and thus drives the positioning of the camera. The complete layer contour is obtained by stitching the single images.

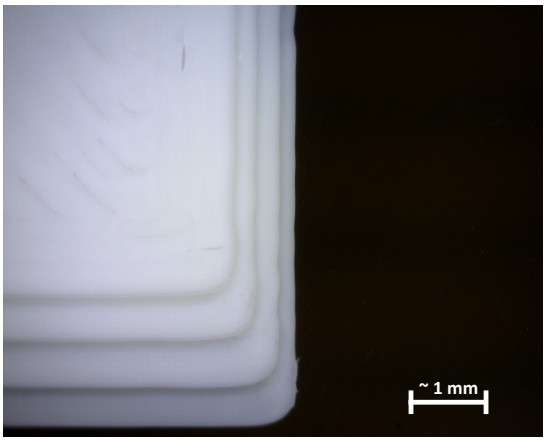

Figure 4. Example image acquired by the microscope, centred on a layer corner of a test part.

Image analysis is tasked with detecting the layer edges in the image. As the operation is challenged by the presence of complex topographic formations belonging to the current and previous layers, as well as by shadows and generally low contrast, a second DT is used to support scene interpretation. In this case, the digital twin reconstructs local layer topography using: nominal information from the part program (extrusion path); numerical simulation of the extrusion process (to compute thickness of the deposited strand); information from the sensors (real extrusion path to adjust the prediction on position of the deposited strands). This information is used by machine vision to interpret the scene based on (simulated) expectations, in order to correctly locate the real edge amongst possible candidates preselected via a Canny-based algorithm [26]. The complete layer contour is obtained by joining the contours detected in the stitched images, as shown in Figure 5.

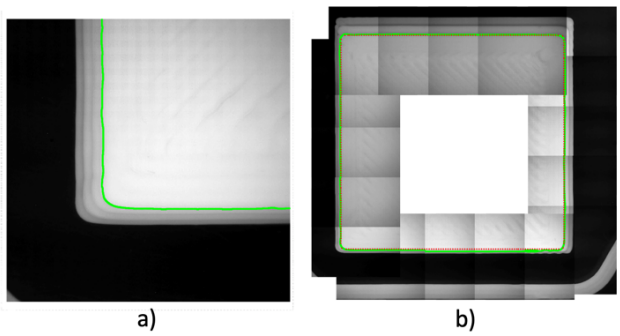

Figure 5 a) result of the contour detection process on a corner, the green line is the detected contour; b) reconstruction of the complete contour for a layer. The stitched images are shown overlaid. The red dotted line indicates the expected contour, the continuous green line is detected one.

As the digital twin is capable of predicting the shape and location of the layer contour for an in-control process, the result of machine vision can be used to also assess if the currently detected contour features any significant discrepancy with respect to the expectation, indicating potential out-of-control conditions [27]. Therefore, the DT is also used to support in-process monitoring. An example is shown in Figure 6, where a corner anomaly is highlighted, due to material over-extrusion. The anomaly can be immediately detected by the monitoring system as an unusual discrepancy between the locally reconstructed edge contour and the expectation produced by the DT.

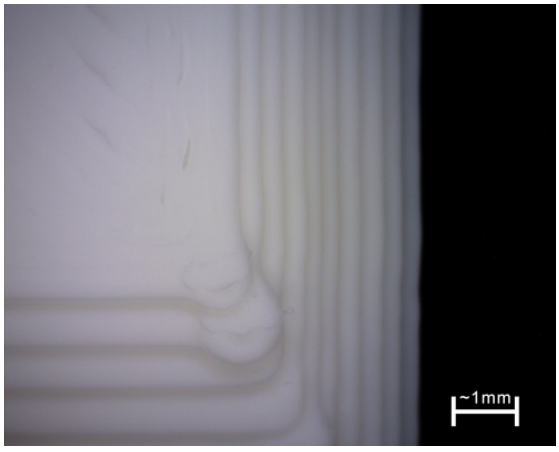

Figure 6. Top view image of a defected pyramid corner, showing the results of over-extrusion.

The geometry of the whole part can be obtained by vertical stacking of the detected layer contours, while the fabrication is in progress. The evolving geometry is continuously compared to the expectations from the DT in order to detect geometric anomalies that propagate through layers, eventually affecting the geometry of the entire part. An example of this is shown in Figure 7. The surfaces of the test pyramid are reconstructed by contour stacking. Colouring is proportional to local distance from the expected surfaces, as simulated by the digital twin. Note how the same local corner anomaly previously described in Figure 6 is also visible in Figure 7 (the red portion of contour visible at the corner of one of the layers).

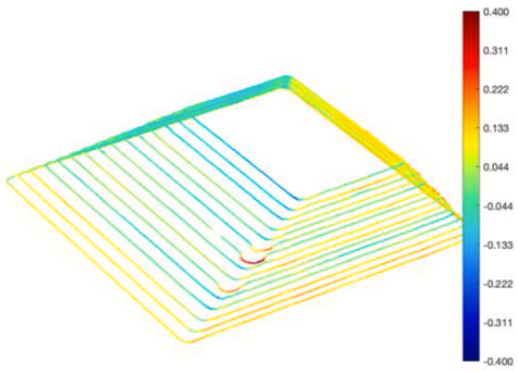

Figure 7. Pyramid surfaces reconstructed by contour-stacking and comparison with the nominal expectations predicted by the digital twin (color proportional to local Euclidean distance (signed, units in mm).

5. Conclusions

In this work the development of an open and modular framework for testing new data analysis methods, multi-sensor data fusion and the use of digital twins for in-process monitoring of FFF has been illustrated. The illustration has focused on the current implementation of two subsystems, one dedicated to layer contour monitoring and making use of machine vision supported by digital twins, and the other dedicated to multi-sensor data fusion for the co-localisation and analysis of process data related to the layer fabrication process. Numerous other possibilities exist to exploit multiple heterogenous sensing and the use of digital twins for automated process monitoring and adaptive optimisation of process parameters.

Particular attention for ongoing and future work is currently given to automated scene interpretation supported by digital twins, where the latter are used to build an expectation of what a scene should look like in nominal conditions, so that anomalies can be isolated. Our research efforts are also currently dedicated to study the integration of mainstream and experimental machine learning technologies into the framework, to explore further avenues for data analysis and processing, and automated decision-making in novel “smart” additive machines.

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