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Optimizing Process Time in Closed-Loop Laser Metal Deposition Processes Using Embedded Software and FPGA Hardware Acceleration

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Abstract

In laser metal deposition processes, a metal powder is melted with a high-power laser source to generate a 3D structure layer by layer. Due to the complex nature of the process, each generated layer presents a non-uniform surface that differs from the theoretical height, introducing cumulative errors in the material growth direction that can significantly impact the quality of the manufactured object. A typical LMD process performs a surface measurement to compensate for the previous layer height errors before the deposition of the material in the new layer. This intralayer measurement phase introduces a time overhead that affects the time needed to manufacture the part. This paper presents a method that minimizes the processing time by reducing the intralayer measurement time by implementing a hardware co-processor implemented in a system on a chip (SoC) with an integrated FPGA. A laser line profiler attached to the LMD laser head that was mounted on an industrial robot has been used to measure the surface as the piece was scanned after finishing each layer material deposition. These allowed to generate height deviations and compute offsets in height and speed to be dynamically applied to the tool path in the following layer material deposition. The validation tests showed satisfactory results as the total process time was significantly reduced by minimizing the layer measurement phase time and eliminating the pre-deposition tool path modification phase as the changes were applied dynamically during the deposition.

Keywords: laser metal deposition, closed-loop control, robotics, embedded software, fpga, real-time, dynamic control.

1 Introduction

Additive manufacturing (AM) techniques have experienced remarkable traction lately in academic and research works. As the underlying technologies have reached an advanced level of maturity, the industry has reliably introduced these processes in real-world applications. Such is the case of laser metal deposition (LMD) processes where a metallic powder can be melted with a high-power laser beam to generate 3D structures layer by layer. However, LMD processes present significant challenges due to the complexity of the process itself, which depends on different parameters such as the speed of powder deposition, applied laser power, powder flow rate or substrate temperature and other physical properties. Consequently, the process experiences two-dimensional dynamics that must be monitored and controlled in-process to obtain acceptable process quality and assure repeatability [1]. These complex dynamics produce a non-uniform substrate growth resulting in an irregular surface between layers that differ from the theoretical deposition height, which introduces an incremental source of error as the layers grow, resulting in parts that do not meet the quality requirements.

In order to minimize these effects, the most common process control systems focus on controlling the distance between the deposition nozzle and the surface. Some techniques apply an open-loop process control approach by applying a toolpath deposition planning to compensate for the predicted overfilling and underfilling based on the modelling of the process [2]. Nevertheless, a closed-loop approach may be required to obtain an improved process quality in addition to the toolpath deposition planning. While real-time nozzle to substrate distance measurements present complex challenges [3], typical closed-loop control strategies rely on the surface measurements between layers. Each layer surface measurement provides a height deviation map from the theoretical model, which is then used for the consequent layer correction [4]. In addition to modifying the toolpath between layers depending on the measured deviation map, some authors modify the speed of deposition using the deviation map measured after the previous layer deposition. As a drawback, these inter-layer modification algorithms present longer process times due to the surface measurement phases [5].

The main goal of this work is to reduce the LMD process time without affecting the quality of the workpiece. To achieve this, we minimize the intra-layer measurement time by implementing the layer correction algorithm in an embedded cladding controller based on a system on a chip (SoC) that combines a quad-core ARM Cortex-A53 and a field programable gate array (FPGA).

2 Methods

The system used in the implementation of this work integrates two main interconnected components: an ABB4400 industrial robot (ABB, Zurich, Switzerland) and the LMD process controller, which integrates a ZCU3EG Zynq Ultrascale+ SoC (Xilinx, CA, USA), a Tachyon 1024 micro-core medium wave infrared (MWIR) camera (NIT, Madrid, Spain) and a Gocator 2440-2B laser line profiler (LMI technologies, MI, USA). While the robot executes the measurement and deposition tool-path movements together with the dynamic deposition speed and height corrections, the LMD controller adapts the laser power by a real-time closed-loop controller using a medium wavelength infrared (MWIR) high-speed camera applying the algorithm described by V. Panadeiro et al. [6]. Additionally, the LMD controller is connected to a laser line profiler used to measure the layers of the work object (WO), compute the deviations in height from the theoretical model, compute the in-process corrections in deposition velocity and height and communicate the corrections to the robot. The typical correction strategy in an LMD process calculates the deposition trajectories between layers [5]. Consequently, the total process time is presented in Equation (1), where N is the number of layers, Tm is the measurement time, Tp is the layer path modification time, and Td is the layer deposition time.

$$T_{proc} = N \cdot \left(T_m + T_p + T_d\right) \tag{1}$$

To reduce the intra-layer time, we propose the following method that eliminates Tp and minimizes Tm. In order to eliminate Tp, the system calculates the height deviations on the fly as the profile information is received from the profile sensor. The work surface is divided into configurable size bins, and the mean height deviation of each bin is computed as the point cloud is being generated. Once the complete mean deviation matrix is generated, the associated deposition speed variations are calculated as defined in Equation (2), where %v is the deposition velocity change percentage from the nominal deposition velocity, $\%v_{max}$ is the allowed maximum velocity percentage change, Δz is the measured height deviation, and Δz_{max} is the maximum height deviation.

$$\%v = 50 + \left(\frac{\%v_{max}}{2} \cdot \frac{\Delta z}{|\Delta z_{max}|}\right) \tag{2}$$

During the deposition phase, having a two-dimensional matrix representing the mean height deviations and the associated deposition speed variation allows the automatic obtention of the corresponding real-time path modification, as the correction matrix acts as a Look-Up Table. On the other hand, to reduce Tm, the point cloud generation and the sensor coordinate transformation to robot coordinates from unit quaternions and tool centre point (TCP) provided by the robot such as in [7] and defined by Equation (3), has been accelerated in the FPGA, allowing to do the computations at the maximum profile sensor rate.

$$P_{WO} = WO_{TCP} \cdot TCP_{ESC} \cdot P' \tag{3}$$

Finally, the point cloud is populated with process metadata such as melt-pool geometry, measured temperatures, or laser power for post-process analysis.

3 Results

The system's performance has been tested using a specimen with a slope that simulates a gradual increase in height. Even though an actual LMD process would never show such errors, the specimen helped validate the point cloud coordinate transformation performance and accuracy. The robot sends the TCP coordinates and the unit quaternions to the control card in the measurement and deposition phases. This information is constantly used to update the direction cosine matrix (DCM) needed to transform the coordinates of the measured surface to robot coordinates and compute the deviations in height. In order to minimize the layer measurement time (Tm), the goal was to calculate the entire profile at the maximum measurement rate (5 kHz or 200 us of sampling period). The two-dimensional profile deviations were implemented in the ARM running at 1.5 GHz and the FPGA with a 200 MHz clock. Figure 1 shows the obtained results comparing the results for three different profile sizes, 2896 points (1 profile), 5792 points (2 consecutive profiles) and 11584 (4 consecutive profiles).

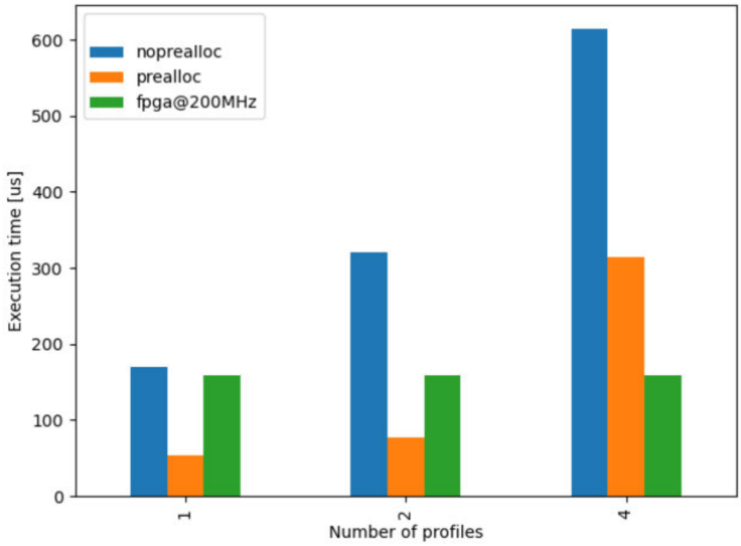

Figure 1: Line profile coordinate transformation processing time comparison: Software implementation without memory pre-allocation (blue), software implementation with memory pre-allocation (orange) and FPGA implementation (green).

As shown in the results, the processing time of the FPGA implementation remains constant for all the sizes at the expense of programable logic resources by implementing multiple instances of the hardware coprocessor for the coordinate transformation. The fastest implementation was in software with memory pre-allocation if just one line profile is used. Nevertheless, the FPGA acceleration scaled better while freeing up the processor resources (memory and processing time), computing the transformation faster than the minimum sampling period time of the line profiler.

The intra-layer path correction calculation phase was removed entirely, eliminating the path planning modification time (Tp). In the material deposition phase, the robot keeps sending the position information (TCP coordinates and unit quaternions), allowing the process controller card to look up the deviation and speed percentage modification values computed in the measurement phase dynamically Figure2.

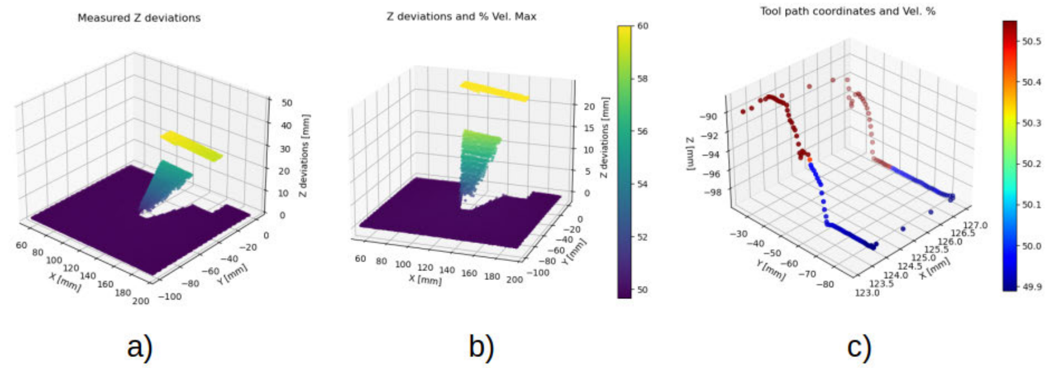

Figure 2: Dynamic tool path modification results. a) Deviations generated from the measurement of the test specimen simulating errors in height, b) Layer toolpath speed percentage change map, c) Dynamic speed modifications commanded to the robot during the deposition phase.

The resulting layer point cloud was populated and stored with the information extracted from the deposition phase for a post-process analysis.

4 Conclusions and Contributions

In this work, we have presented an optimization method to reduce the cycle time of an LMD process by eliminating the intralayer tool path modification phase and implementing the deviation calculation and coordinate transformation logic in parallelizable FPGA co-processors directly in the embedded LMD control card. The hardware acceleration for the coordinate transformation of the received point cloud allowed minimizing the intralayer measurement phase as the sensed profiles were transformed on the fly at the sensor maximum sampling rate. The FPGA implementation scaled well with the increase of the number of profiles, allowing multi-sensor setups. The proposed system can thus modify dynamically the height deviations caused by the previous layer by commanding height offsets and variations in the nominal speed of the tool path during the deposition phase depending on the coordinates reported by the robot. We have also presented the validation setup and the obtained results for a test specimen that simulated height errors in the layer that validated the proposed process time optimization method. In addition to this, the generated point cloud was stored, merging several process metadata for ex-post process analysis. In addition to measured profile coordinates and the deviations in height, the recorded layer point cloud stores critical process information such as the measured temperature field measured by the coaxial camera, melt-pool geometry information, and other process data.

Future work will be focused on different approaches to eliminate the intralayer measurement phase by applying an in-situ profile measurement during the metal deposition. Consequently, further work must be done in optical design and filtering mechanisms combined with proper signal and image processing. Additionally, novel control mechanisms and data fusion techniques will be studied for their application in complex closed-loop control systems to improve the quality of the LMD process using artificial intelligence and machine learning algorithms, such as reinforcement learning techniques.

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