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Digital Twin for Additive Manufacturing and Smart Manufacturing Education

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Digital Twin for Additive Manufacturing and Smart Manufacturing Education

Abstract

The increasing adoption of additive manufacturing (AM) or 3D printing across different industries indicates the importance for educational institutions to incorporate this technology into their curriculum. This ensures that students are adequately prepared with the skills and knowledge needed for future career opportunities. One crucial task is to teach students how to use modern technology to evaluate the quality of AM parts because AM has not reached the point of competing with traditional manufacturing in terms of surface finish and repeatability. Moreover, the printed parts are often treated as black boxes with invisible defects, such as pores and cracks. Such non-transparency significantly challenges the qualification and certification of additively manufactured parts. In this paper, we present a semester-long project designed for a new AM course offered at University A to demonstrate the challenges and benefits of AM. At the beginning of the project, we teach students how to develop a digital twin of the 3D printing process. This is later used to provide in-situ monitoring of the process and visualize the internal defects towards predictable quality control of the printed parts. Through changing process parameters, students will learn how to optimize part quality and how` defects in parts can be eliminated using the digital twin. This paper presents a reference implementation with technical and pedagogical details for the education community.

Introduction

The use of additive manufacturing or 3D printing has greatly increased in various industry sectors in the last five years. This is because through AM technology, complex geometric shapes, multi-material, and multi-functional parts can be additively manufactured in a single operation which is a significant advantage over conventional manufacturing processes. Over the past two decades, the intensive research carried out on AM technologies has yielded tremendous progress in the development and commercialization of new and innovative AM processes, such as Fused Deposition Modeling (FDM), selective laser sintering, and other rapid prototyping methods, as well as numerous practical applications in aerospace, automotive, biomedical, civil, energy and other industries [1]. Many manufacturing industries have realized the benefits of AM technology and started utilizing it as an integral part of their processes [2]–[4].

Some educational institutions began offering AM courses in their curriculum[5]. For example, a study published in 2021 presented how a new AM was offered at University B. The course reviewed various AM processes. It explained how AM facilitates the creation of complex geometries, often without many constraints present in traditional manufacturing methods. Given all these advantages, AM still contains many challenges. This is because the 3D-printed parts are often treated as black boxes with invisible defects, such as pores and cracks. Such non-transparency significantly challenges the qualification and certification of additively manufactured parts.

An alternative solution to this challenge is building a digital twin of 3D printing equipment and printed parts. The central concept of a digital twin or digital replica is a dynamic virtual representation of 3D printing hardware[6]. This representation can be classified at different levels.

In general, the term "digital twin" refers to a digital representation of a given asset that comprises engineering models and design standards outlining its geometry, components, and behavior[7]. More importantly, it also contains information particular to the physical asset that it represents, such as as-built and operational data.

Implementing digital twins in 3D printing processes benefits industries as it simulates the entire building of 3D parts and identifies whether there will be printing defects and where they may occur. If successful, this approach can be used to correct the 3D model. The digital twin is becoming widespread in the industry due to the emergence of smart sensors, the Internet of Things (IoT), Industry 4.0, and better capability in synthesizing a lot of data via cloud computing and simulations[8]. However, digital twining for 3D printing processes has slowly developed to its full potential in educational institutions. It is the responsibility of educational institutions to support efforts to embed this technology in their curriculum to prepare students for the future. As such, one crucial task is to teach students how to use modern technology like smart sensors and IoT to evaluate the quality of AM parts. This makes AM closer to the point of competing with traditional manufacturing in terms of surface finish and repeatability.

At University A, a new AM course is designed and offered in the Mechanical Engineering Technology Department. We integrate digital twin technology in this course for the first time to help our students thrive in today's fast-paced industry. In this paper, we will discuss the most important elements of the project and how we instruct the student to fulfill the required tasks.

A semester-long project

In this paper, we present a semester-long project designed for a new additive manufacturing (AM) course offered at University A to demonstrate the challenges and benefits of AM. At the project's beginning, we teach students about digital twinning in 3D printer and printing processes, covering key aspects like quality control, sensor integration, monitoring printing progress, and optimizing printing parameters. Digital twins enable visualization of the 3D printer and printing process, which allows students to observe the machine's operation in a virtual environment. This visualization helps in understanding how the machine functions, including movements of the print head, deposition of layers, and interactions with materials. Quality control of the printing process will be taught via digital twins to predict defects based on printing parameters. Sensors also will be integrated into digital twins which enables real-time monitoring of parameters like temperature and humidity, which in turn it provides insights into printing defects and flows. Students will learn to track print progress and adjust parameters such as layer thickness and print speed through digital twinning, optimizing outcomes.

As shown in Figure 1, this project contains four modules, (1) developing the mechanical digital twin of an extrusion-based 3D printer, (2) developing the process digital twin considering the printing path and extrusion physics, (3) leveraging multi-modal sensors to monitor the printing processes, including the XYZ stage encoder for the print head position, nozzle temperature, and a close-up camera mounted on the printhead, and (4) using AI to predict the printing status and quality.

Ultimately, students will develop a high-fidelity digital twin with real-time feedback data. The digital twin is a 3D-rendered simulation of the printing path, updated and synced with the physical printing status. The printing path is color-coded by many factors, such as printing status, deposition width, deposition location error, deposition temperatures, etc.

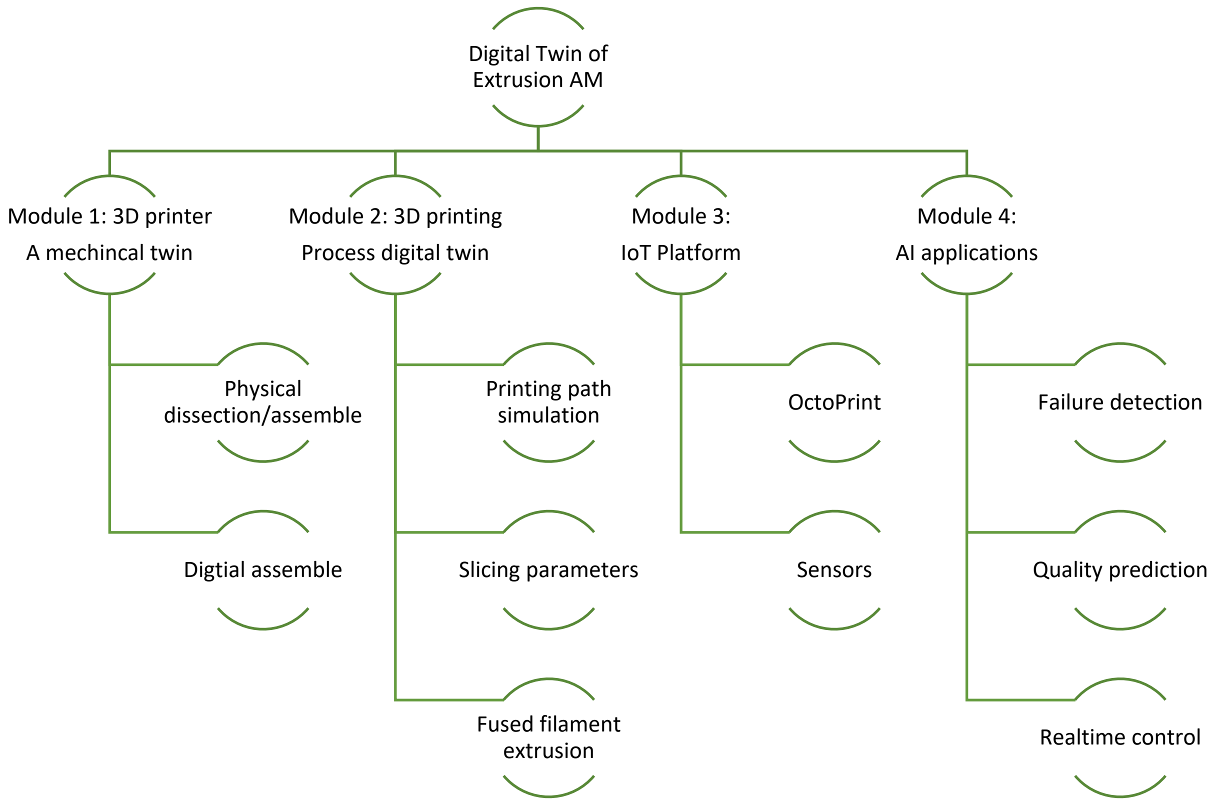

Figure 1: Four project modules in the semester-long project

Module 1: Mechanical digital twin of an extrusion-based 3D printer and printed parts

Students need to understand the mechanical design of a 3D printer. Hence, we will provide a three-week-long lab for students to develop the digital twin of the mechanical system of a 3D printer.

We group students into teams and let each group dissect a Prusa 3D printer (*Prusa i3 MK3S*) into individual components. Students will have access to 3D CAD models of all these components. They will be asked to record the dissection and physically and digitally assemble the components. The digital assembly will be the developed digital twin for the 3D printer. All the Solidworks models are accessible from GrabCAD[9]. The assembled CAD model in Solidworks will be the digital twin of a 3D printer, as shown in Figure 2. Through this lab activity, students will better understand how to build a 3D printer and, more importantly, how to underline mechanical design.

Figure 2: Develop the mechanical digital twin of the 3D printer by dissecting and assembling physically and digitally

Module 2: Process digital twin of an extrusion-based 3D printing

Extrusion-based 3D printing process leverages heat to fuse the input filament and deposit it to previously printed layers. This process involves multi-physics, including thermal, structural, and materials.

To improve students' learning of the "additive" concept, we let them touch the "manufacturing" process, by using "Lego bricks" to simulate how a part in being built. Students are grouped into team, each team is allocated 400 lego blocks, as shown in Figure 3. In this lab activity, students need to use lego to build a cone layer by layer. Specifically, they will:

- Plan building into layers: Students will determine how many layers to build the given cone 3D model using lego bricks. They will draw the contour of each layer, which simulates the layer slicing in additive manufacturing. Students will understand the concept of "layer"
- Building: Students will fill the contour with available blocks, which emulate the concept of "Infill pattern" and "hatch space" in additive manufacturing.
- Inspection: After "printing" the cone using lego brick, students are asked to think about methods to quantify the shape deviation of the "printed" lego part from the designed cones. One viable metric is the difference between the volume of lego part and the volume of a designed cone.
- Drop test: Lastly, students are invited to drop their lego part with the cone tip pointing down. Students will record and compare the heights their lego build can survive. In this test, students will understand the concept of common failure mode in printed parts.

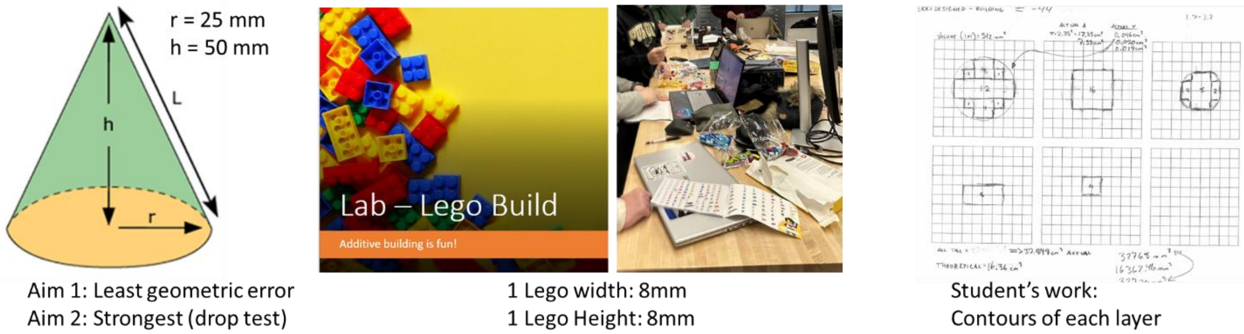

Figure 3: Lego build to physically simulate additive manufacturing.

Beyond the physical twin of additive manufacturing, a simulation of the printing path will facilitate students understand how the materials are deposited and "glued" together. The concept of "additive" manufacturing will be discussed using the simulation of printing paths. Also, such a process digital twin is an excellent tool for students to understand the impact of slicing parameters.

We will utilize slicing software as the digital twin for the process. Specifically, Simplify3D or PrusaSlicer can be used. Students will experiment with different slicing parameters and compare the results. Figure 4 shows a 3D "Benchy Boat" model sliced into printing tool paths. This 3D model was downloaded from Thingiverse.com. By exploring the printing paths, students will better understand the concepts of slicing parameters, such as layer thickness, infill patterns, hatch space, and so on. Through changing process parameters, students will learn how to optimize part quality and how the defects in parts can be eliminated using the digital twin.

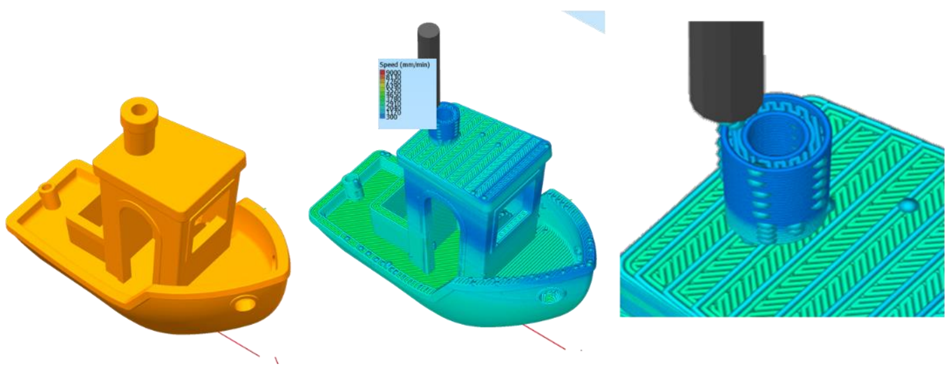

Figure 4: Process digital twin of 3D printing: the printing paths

Besides the tool path simulation, we can also instruct students to conduct a simulation of the deposition process, i.e., the process that which the filament is extruded from the nozzle and deposits and bonds with previous layers and paths. This simulation can let students explore different printing processing parameters on the printed part surface quality. The instructor will scaffold the simulation using the model in OpenFOAM developed by Liu [2]. As such a simulation model is quite complex, we intend to use this simulation as a bonus project for interested students.

The simulation of printing paths combined with the mechanical systems serves as the primary digital twin for 3D printing. In the rest of the paper, we will synchronize the digital twin with the realtime data from sensors and inferred information from the sensor data (such as printing status and quality).

To measure students' understanding of process parameters, a lab activity on slicing software will be conducted: Students will leverage the slicing software and slice a given 3D model using three different layer thickness (0.1mm,0.2mm, and 0.3mm). They will use the slider to visualize the tool path and compare the surface textures of different layer thickness. Also, they will summarize the total printing time, and number of layers under different layer thickness into a table. After 3D printing, they will physically measure four key dimensions of the provided 3D model and compare them with the designed values.

Module 3: The Internet of Things (IoT) Platform to connect the digital twin and physical world

The above two digital twins receive no feedback from the physical world. This module 3 guides students to explore and appreciate the benefits of feeding real data to the digital twin. Specifically, we will leverage the IoT data to predict printing reliability and quality and detect defects based on the realtime camera.

Figure 5 shows a IoT platform and all the sensors on a Prusa 3D printer. The microcontroller, Raspberry Pi, is a server to control the 3D printer and interacts with users through a WIFI connection. It can report nearly all the printing statuses, such as XYZ positions, temperature, and printing progress. The motor driver, TMC2130, can give feedback on the current and skipped steps, which are useful for detecting printer crashes. Two cameras (Logitech C270 and a low-cost webcam) monitor the closed-up nozzle and image an entire layer. The IR filament sensor can detect whether the filament is stocked or not. The MEMS microphone installed in the Logi 270 camera senses the acoustic emission of the printer.

Students remotely access the printer and the sensor data using an open source platform OctoPrint[10]. Each 3D printer will connect to a Rasberry Pi, running the OctoPI operation system. A web-based interface will be used for the students to interact with the printers, such as extracting sensor data and sending G-Codes to control the printer.

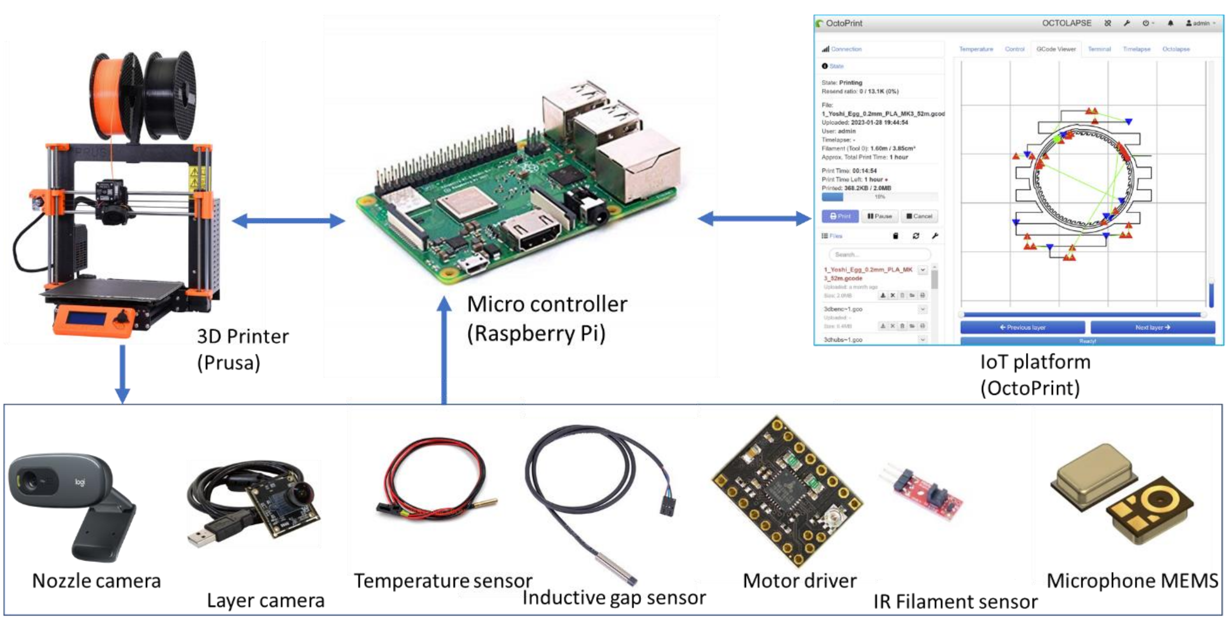

Figure 5: IoT platform and sensors installed on a Prusa 3D printer

Module 4: Artificial Intelligence (AI) applications

In this module, the digital twin and the IoT platform are seamlessly integrated to generate values for the 3D printing process. Empowered by AI/Machine learning algorithms, the sensor data can be actively leveraged to perform real-time prediction on printing status and part quality. This module will be further decomposed into multiple applications using different sensors.

Application 1: Realtime monitoring of 3D printing status

3D printing sequentially adds materials, defects, and failures in any layers. This may fail the entire printing if it exceeds the critical limit. In this regard, timely detection of unsuccessful layer printing will significantly save waste material and time. In this course project, students will classify the printing status into three categories: normal printing, printing failure, or printing completed. Students can choose different approaches. The first approach is using the close-up camera that images the nozzle extrusion. Students apply a computer vision algorithm [11], to classify the printing status and detect printing errors timely. The low-cost web camera Logitech C270 is modified by tuning the camera's focus, then mounted on the extruder to directly image the nozzle extrusion. Figure 6 shows image samples of normal printing and failure. In the image of failure printing, we can see the extruded material is not deposited on the previous layer but hanging in the air. This pattern can be easily detected using the algorithm[11].

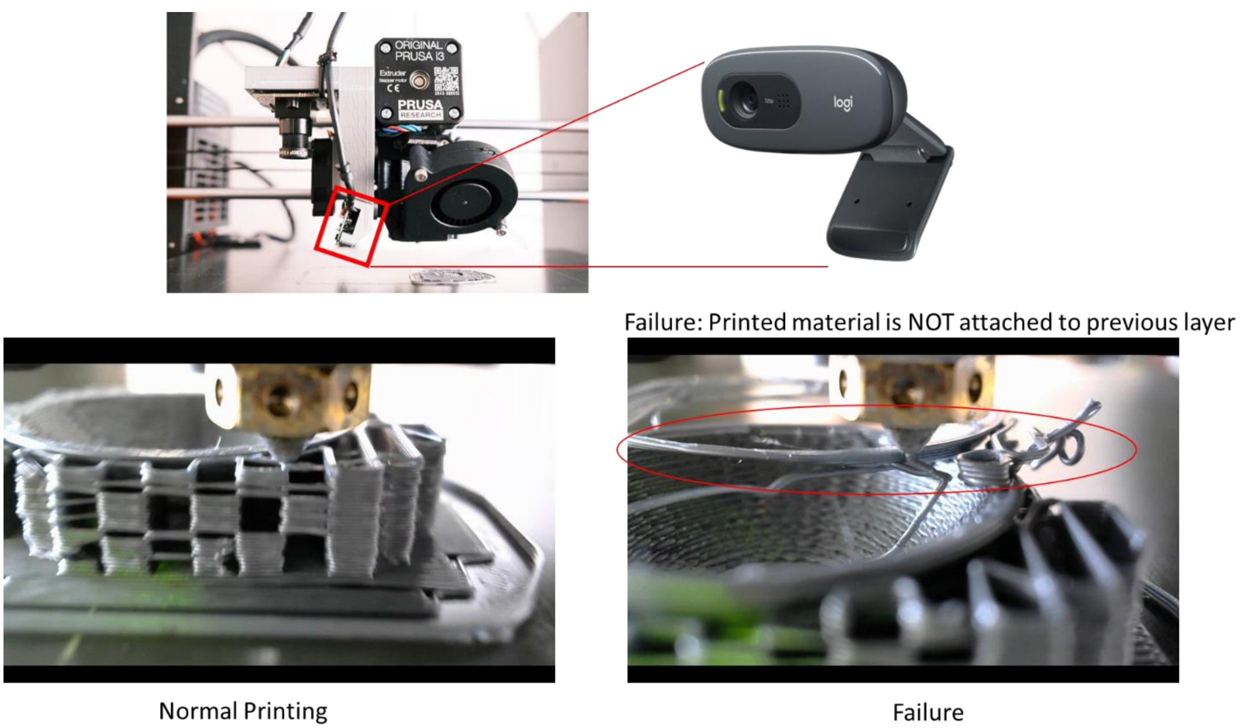

Figure 6: A close-up camera to image the nozzle extrusion for failure detection.

The second approach is based on acoustic emission from the microphone in the same Logitech C270 camera above. In this approach, students must collect their own signal data set and manually label it. Students will conduct Fast Fourier Transformation (FFT) on the sensed audio signal using MATLAB and build a linear regression model to classify the acoustic signal into three types, normal motion, crash, or no motion. Figure 7 compares the FFT results of three different printing statuses. The crash signal has a very high frequency of 700 Hz, while the no-printing signal has nearly zero power in the 600 -700 Hz range. Compared with normal printing, the crash signal has a different power distribution in the 600 -700 Hz range. Machine learning algorithms will be used to differentiate these two different statuses. Therefore, this simple example shows the feasibility of using acoustic emission to infer the printing status.

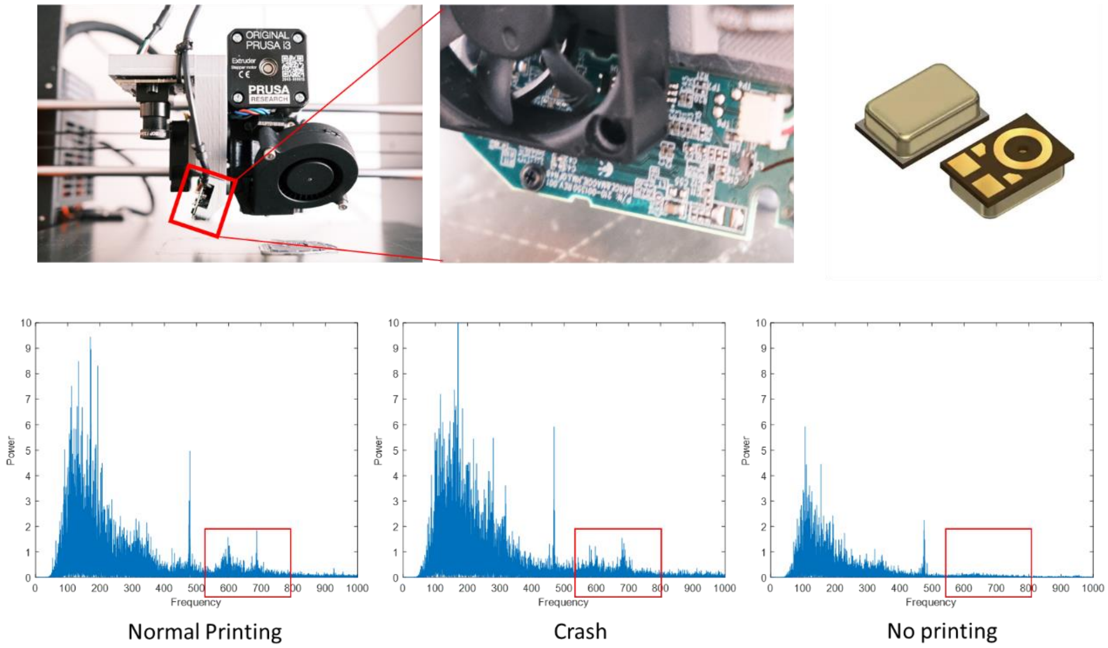

Figure 7: Acoustic emission can be used to detect printing status.

Application 2: Quality prediction

The internal defects in 3D printing significantly impact the parts' strength. To accurately predict the part strength, in-process monitoring is critical[12]. In this application, students will use the installed camera to take a photo of the printing surface after every layer is completed. Figure 7 shows a low-cost web camera mounted on the extruder. We use the Octolapse plugin in the OctoPrint[10] IoT platform to program the camera. After every layer, i.e., the Z coordinate is about to increase in the G-Code, we will send an extra GCode to the printer so that the camera on the extruder will move to the center of the printing area and take a photo of the printed surface.

As shown in Figure 7, this low-cost camera has severe distortion, and we use MATLAB camera calibration[13], [14] to calibrate the camera and successfully correct the image distortion. Students will be given calibrated images to conduct computer vision algorithms. They will be guided to use the multi-head neural networks [11], [15] to calculate the deviation from optimal printing parameters. The instructor will scaffold the MATLAB code of camera calibration[13] and the Python code of multi-head neural networks based on the open source code[15].

In this project, students will see how the actual 3D print deviates from the designed tool path. It will help students understand why there is a vast variation from part to part in 3D printing, as the path deviations are randomized mainly.

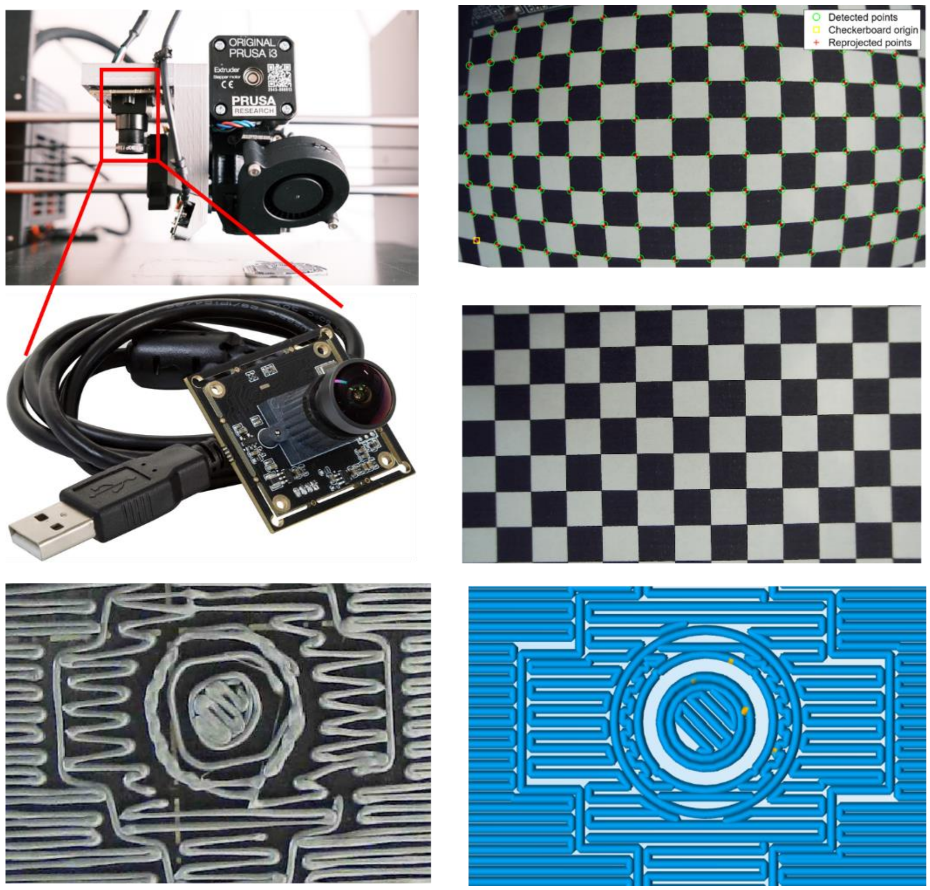

Figure 8: A camera is used to image the printing surface for every layer

Application 3: Realtime printer control

This last application explores the ultimate goal of a digital twin for additive manufacturing: real-time control. The previous two applications enable students to infer the printing status. Corrective actions need to be taken if failure or defects are detected. Specifically, we will intentionally modify the normal G-Code by injecting attacks, including low nozzle temperature, abnormal extrusion rate, and incorrect layer thickness.

In this project, we will pause the printing after each layer is printed and let students adjust the printing parameter manually and with programming. In the manual adjustment, we will show all the observed data and allow students to adjust the printing parameters online using the OctoPrint. Figure 9 shows the information provided to students. Such hands-on adjustment will help students fundamentally understand the effect of different printing parameters. Then the instructor will showcase the code to automatically adjust the settings using the AI algorithm[11].

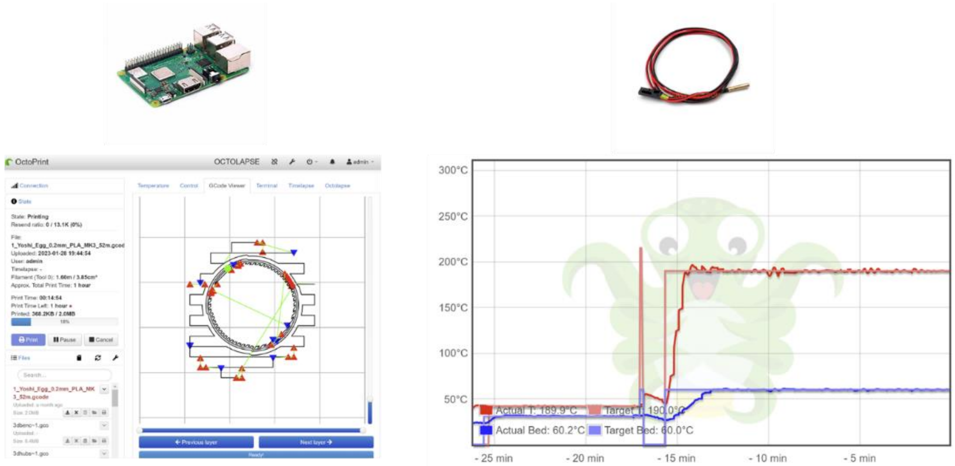

Figure 9: Realtime control the printing parameter using OctoPrint

Course offering and evaluations

The authors offered this course in Spring 2024. There were 12 students enrolled, grouped into 4 teams. Each team was allocated a 3D printer. Module 1 lasted three weeks, and each team was allocated a 3D printer. In week 1 of Module 1, the author gave a lecture on the technologies and components required to form a 3D printer. Then students spent one week assembling the printers from components. In week 3 of Module 1, students worked on printing test samples, which included troubleshooting 3D printing.

This course will be evaluated by the end of the semester. Ten common questions will be asked to evaluate the course:

- The course is well organized.
- The assignments aid me in achieving the course objectives.
- The projects or laboratories aid me in achieving the class objectives.
- The tests or exams aid me in achieving the course objectives.
- The instructor communicates clearly.
- The instructor effectively answers students' questions.
- The instructor seems to care about my learning in this course.
- The instructor makes time to help students.
- The instructor is fair in evaluating my performance in the course.
- The instructor created an inclusive learning environment.

Along with the 10 common questions in the survey, we will include more specific questions. To what extent students will agree with the following statements:

- Lego build lab helps you understand the AM process better.
- Building 3D printers let me understand the mechanism and printing principle of AM better.
- The slicing software assists me in understanding the concepts in AM, such as layer thickness, hatch space, and tool path.
- The Octoprint IoT platform let me appreciate the use of digital twins in the AM process.
- The layer-wise images for the printing process let me understand deeper of the quality issues in AM.

- The detection of printing failure helps me understand how AI can help manufacturing.

Conclusion

This paper presents a reference framework to teach students how to implement and utilize digital twins for additive manufacturing. It first guides students to develop the mechanical digital twin of an extrusion-based 3D printer by dissecting and assembling a 3D printer physically and digitally. Then the slicing software is utilized as a digital twin for printing. Students can understand the concepts of printing parameters, such as layer thickness and hatch space, and explore the effect of these parameters on printing efficiency and quality. Moreover, students will be instructed to build an IoT platform to manage the sensor data, which will feed into the digital twin. Lastly, students will leverage the scaffold AI algorithms to infer the printing status and quality from the sensor data, based on which they can timely adjust the printing parameters for better printing. This reference course project can be used in additive and smart manufacturing courses.

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