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3D Bioprinting on Moving Surfaces Using Computer Vision

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Abstract—3D bioprinting is a rapidly developing field with many potential applications in medicine, bioengineering, and, possibly, even other areas. However, one of the main challenges in bioprinting is maintaining accuracy and precision during the printing process, especially when printing on a moving surface. The moving surface terminology means a not properly fixed or unstable surface for printing. For example, a human body, healing harmed tissues directly in an ambulance on the way to the hospital or any other emergency. This paper proposes a novel method for 3D bioprinting on moving surfaces using computer vision and machine learning. The approach involves the use of video processing techniques to analyze the bioprinting process in real-time, enabling the identification of potential issues and the adjustment of the printing process to improve the quality of the printed tissue. This is an important step toward the development of scalable and reproducible bioprinting technologies for tissue engineering applications.

Keywords: 3D bioprinting; 3D printing on moving surface; computer vision; machine learning; video processing; quality assurance; real-time analysis;

I. Introduction

The use of 3D printing on moving surfaces has the potential to enable the production of functional tissues with complex geometries and microstructures. In this article, we consider the problematic situation such as the motion of the surface can disrupt the printing process, leading to defects in the printed tissue. To overcome this issue, it is necessary to develop strategies for controlling the printing process on the fly, considering the surface's motion. This is where computer vision and machine learning come into play.

A. Computer Vision

Computer vision is a field of artificial intelligence and computer science that focuses on enabling computers to see, interpret and understand the visual world. It involves the development of algorithms and techniques that allow computers to process, analyze and understand digital images and videos in a way that is like how humans perceive and interpret visual information.

The computer vision technique is used in a wide range of applications, including image and video analysis, object recognition, facial recognition, robotics, and medical image analysis.

B. Bioprinting

Bioprinting is a process that involves using a 3D printer to create a biological structure by depositing living cells layer by layer. It has the potential to revolutionize the field of medicine by allowing scientists and medical professionals to create customized tissues and organs for use in transplants and other medical treatments.

One of the main potential applications of bioprinting in medicine is to create replacement tissues and organs for patients who need them due to disease or injury. For example, bioprinting could be used to create customized skin grafts for burn victims or to create new liver or kidney tissue for patients with organ failure.

C. Computer Vision in Bioprinting

Computer vision plays a crucial role in the successful implementation of tissue printing. Machine learning algorithms can be used to analyze video feeds of the printing process, allowing for the detection of any defects or abnormalities in the printed tissue. Additionally, computer vision can be used to track the movement of the surface on which the tissue is being printed, allowing the printer to adjust the printing process in real time to ensure the accuracy and precision of the final product.

Therefore, the application of computer vision in 3D bioprinting on moving surfaces is essential for quality assurance, and the ability to adjust the printing process in response to surface movement. It is a key technology that will enable the continued development and advancement of this exciting field.

Herein we cover:

- System Design – the requirement for the project setup.
- Methodology – what approach we use and why.
- Results – 2D examples of ROI detection and movement estimation.

II. SYSTEM DESIGN

The final product has specific requirements. In addition to software, it is necessary to account for cameras, light setup, printer type, and 3D scanner. We described general information about the hardware setup below.

A. Cameras

Two cameras work together to capture a more comprehensive view of the object, allowing for better analysis and understanding. They must be manually placed on:

1) *Top:* Captures the width and height (X- and Y- axes) of the surface.

2) *Side:* Captures its depth (Z-axis).

The top and the side cameras are used to provide one side of a 3D reconstruction of the object [1]. Having a human vision helps to adjust the side camera angle to capture different wound views; thus, we can ensure that the required side of view will not be blocked by any object. The top view is not required adjusting; it is always perpendicular to the wound and has the main field of view.

The cameras are synchronized to perform accurate tracking of the printer position and detect movements of the surface at the same time on both views. It means that they are required to have the same FPS. At the same place, calibration is an important camera configuration. It is required to create one common coordinate system – world coordinates, because of different view image fusion. That helps to have the actual world position of the printer and its path.

B. Light

It is important to place the light sources, so they evenly illuminate the area of interest from multiple angles to avoid shadows.

1) *Multiple light sources:* Using multiple light sources with different angles and intensities can help to illuminate the area of interest evenly and reduce the likelihood of shadows.

2) *Diffused light:* Using diffused light, such as through a softbox or translucent panel, can help to reduce harsh shadows and create more even lighting.

3) *Reflectors:* Placing reflectors strategically around the table will also help bounce light, brightening the shaded areas.

It is possible to remove or reduce the appearance of shadows in images using computer vision techniques, but it is not a trivial task, and it can be challenging to completely remove all shadows. The main approach to removing or reducing shadows is by image processing techniques: image enhancement, restoration, and segmentation. But main issues can arise when attempting to remove shadows in this way. All of them are very important to our project:

- Information loss: Shadows can contain important information about the shape and position of objects in an image. Removing shadows completely can lead to the loss of important information and affect downstream tasks' performance.

- High computational cost: The process of removing the shadows from an image can be computationally expensive and time-consuming. The program should work fast enough to capture each micro-movement immediately without lagging.

C. 3D Scanning

Scanning is required to get the polygon of the harmed area. A 3D model of the area is an input to the 3D printer; additionally, we get a region of interest (ROI). Later, the role of ROI will be discussed in detail. Scanning is a vital part of the system and is used only once at the beginning of the operation.

Generally, there are two ways to find out area shape: scanning (LiDAR, laser, structured light, photogrammetry), and using Deep Learning. The aim is to capture 3D data on the human directly.

1) *LiDAR and laser scanner:* These techniques are accurate and reliable, but not a fit for our case. One of the main reasons is the resolution, laser scanning typically captures a large number of points [2], while we are oriented on small – mid-size shapes.

2) *Structured light:* This technique projects patterns of light onto an object and uses a camera to record how the pattern is deformed by the surface. The deformation is used to calculate the 3D shape of the object. It's used to scan objects with complex shapes or surfaces that are difficult to capture with other techniques. There are various types of such scanners: from huge setups to handheld apparatus [3]. And this is the best thing about it because the ambulance is not big enough to hold a number of big-sized pieces of equipment.

3) *Photogrammetry:* It uses mathematical algorithms to extract 3D information from 2D images and calculates the spatial relationships between objects and their surroundings.

There are neural network algorithms that can build 3D models from 2D videos or images [4], but most of them are computationally and time expensive or trained on large/convex objects, which is the opposite of our problem. However, we found a purpose for using Deep Learning (DL) – to implement scan post-process. Any of the scanners capture the whole picture of the surface - not only the wound but the background too. A DL model is designed to segment one wound shape out of the background or other wounds. As the alternativity to the DL model, there are different foreground extraction algorithms, such as GrabCut [5]. This is a fast solution choice, but it might be inaccurate (cropping the right pixels, keeping background) or require additional human efforts.

D. 3D Bioprinter

The project requires a flexible printer – a robotic arm with the option to print several materials at once [6].

III. METHODOLOGY

Having the background of the required setup helps to understand the software development process.

Our focus is to provide an accurate and fast real-time analysis and actions. The system has automatic control over the cameras' videos and the 3D bioprinter.

A. Input Data

One of the most important steps is to configure the data process. Data we have as an input: two live videos, 3D mesh, and printer's capabilities.

As it was explained, the videos must be synchronized – the timeline for each frame of video A must match all the frames of video B. To achieve it, we process each video as a separate thread, so we are sure that the program reads video A-frames simultaneously with video B.

We cannot directly process the output of the 3D scanner; first, we converted it to the python format (numpy array). Python programming language is famous for its various libraries, trimesh or stl library easily converts the 3D geometry to an array with the coordinates for the next processing.

The printer's capabilities are constrained. The variables we integrated into the analytics include nozzle diameter, printing speed limitations, min/max flexion/extension angles of the robotic arm.

B. Pre-printing Stage

At the earliest point, we created a clear environment for a better focus on the required part of the surface: removing the background, as it's noise. This means clarifying the ROI, cropping the image to get only the harmed area picture, help to segment the area to treat only the printing area as the target object. As it was mentioned before, getting a ROI requires a scanned mesh as the input, specifically, the top view (for the top camera) and the side view (at the angle of the second camera). The last layer (polygon) of the mesh is a contour of the wound. We got a bounding box of the wound using the computer vision method such as finding contours.

Right before printing started, there was generated an initial trajectory. So, we had the shape and area of the lesion, converting them to a set of consistent points (checkpoints) – one point per video frame. Having the printer's coordinates, we matched them with the expected coordinates, to validate the correctness of the printer's path.

C. Printing Stage

In the printing stage, for every frame we:

- Detecting movements.
- Updating initial trajectory coordinates. Dynamically update the array of passed checkpoints, to avoid printing again the tissues, which were already being printed.

Surface movements were detected and tracked with the optical flow method [7]. This method, in combination with the camera's calibration, can estimate movements precisely and return the world coordinates of the displacement.

The surface's moving is not a continuous process and cannot be averaged. After the movement was detected, the system is predicting possible next velocities to adjust the printer's coordinates ahead of the curve. This was done using Kalman Filter.

The last step in the main process is ignoring the moving nozzle and printed materials within the segmented ROI to avoid false triggering.

D. Analytics

Analytics is basically a wrapper for the whole system – it covers both pre- and main processes, but another purpose is making decisions and optimizing processes.

Analytics was used to process if the distance between the nozzle's coordinates and true trajectory is far (or close) enough to move the nozzle – either to continue processing and printing or stop it and wait for the environment to meet the printer's capabilities. Together with the trajectory prediction and estimated surface movements output, based on the decision, it updates the coordinate points and validates a new trajectory with the initial one.

Optimization of bioprinting is a tradeoff between printer speed and filament discharging. The issue is to finish the printing as soon as possible but circumvent material gaps.

IV. Results

The results of the study include 2D examples of movement detection and estimation.

Test environment:

- Camera: 29.91 FPS, 1280x720.
- Shaking table: Quanser Shake Table II (earthquake simulator).

Firstly, an example of the ROI pipeline is represented in figure 1.

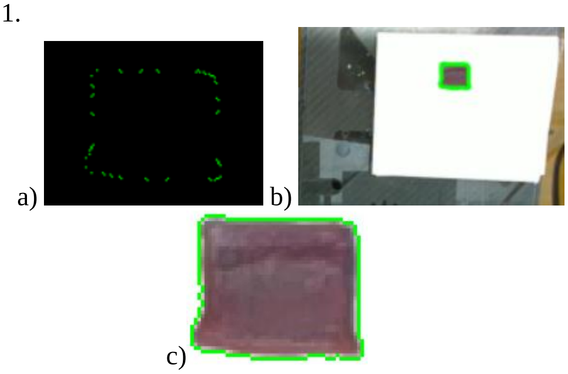

Figure 1. ROI pipeline: an input shape example (a), detection (b), and cropping (c)

Tiny cropping is similar to a strong magnification. It improves pixel-wise focus, so each twitch is noticeable.

For movements, estimation has experimented with two frequencies (Fig. 2):

- 0.1 Hz, which is, in respect of the camera's characteristics, 0.08 mm per frame (one frame equals 0.03 s timestamp).
- 0.5 Hz – 0.47 mm per frame.

Need to mention, while the camera captures every 0.03 s, the vibration table lies in every 0.0005 s, which makes a ground truth data plot (Fig. 2, column 1) look smoother.

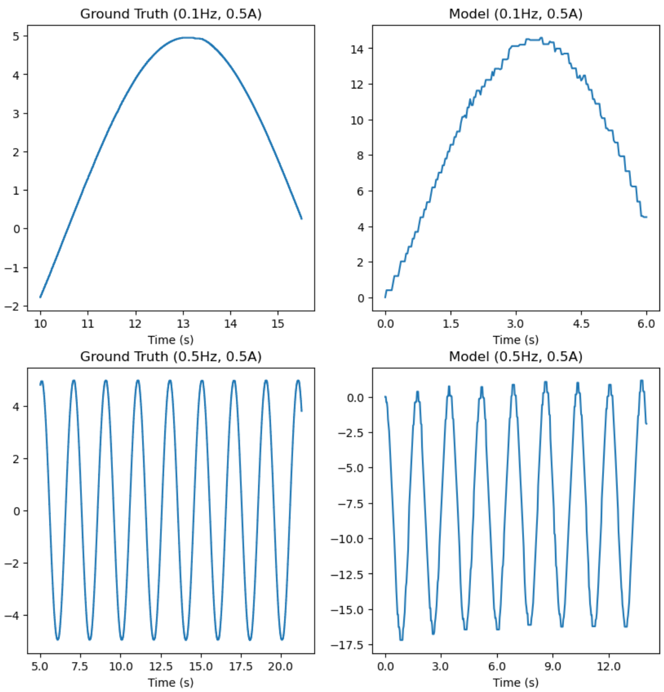

Figure 2. Model performance compared to ground truth data gathered from the shaking table. Row 1 – 0.1 Hz, row 2 – 0.5 Hz. Table position (ground truth) is measured in mm, but model movement estimation is in px.

Positive and negative values point to moving to positive (right) and negative (left) X respectively. On the plot (fig. 2), we calculate cumulative movings to recreate the vibration table path, when the algorithm returns only a pixel displacement between two frames.

Even taking into account that the movements occur on only one axis (X-axis), the visual representation is still expressed in 2D, because the camera is not fixed at a perfect angle, as can also be seen in a real situation. So there are also movements for the Y-axis, albeit close to 0.

V. Conclusions

The paper discusses the use of machine learning techniques in 3D bioprinting on moving surfaces. Bioprinting is a process that involves using a 3D printer to create biological structures by depositing living cells layer by layer. Nevertheless, the surface movement might interfere with printing, resulting in imperfections in the printed tissue. The authors suggested using computer vision techniques to manage the printing process instantly while taking the motion of the surface into account in order to solve this problem. The system design is covered in the paper, along with the hardware configuration, cameras, illumination, 3D scanning, and methodology. The study's findings include 2D illustrations of movement estimates and ROI identification. Overall, computer vision is a critical technology that will enable the development and advancement of this fascinating sector. It is essential for quality assurance and the ability to modify the printing process in response to surface movement in 3D bioprinting on moving surfaces.

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