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3D PRINTING ERRORS DETECTION DURING THE PROCESS

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ABSTRACT

Automated error detection in 3D printing is an important challenge that impacts not only the quality of the final parts but also operational efficiency, helping to minimize wasted time and material. Certain types of errors can even result in printer malfunctions. A widely used solution for monitoring the printing process involves employing a webcam to observe the process in real time, either alerting the operator or halting the print if an issue is detected. In this paper, a computer vision algorithm able to detect specific errors is proposed.

KEYWORDS: 3D printing, errors, detection, machine learning

1. Introduction

Unmanned error detection in 3D printing is a critical issue that affects not only the final quality of produced parts but also operational efficiency by reducing wasted time and material consumption. In many applications, printing errors can be caused by various factors such as: nozzle clogging [1-3], first-layer adhesion issues [4-5], irregular filament extrusion [6-7], positioning errors [8-9], or even mechanical failures of the printer [10].

Introducing a webcam into the printing process for real-time monitoring and error detection can significantly improve product quality and reduce waste.

3D printing errors can be classified into various categories: extrusion problems, nozzle clogging, delamination, layer shifting, print bed adhesion issues.

One of the most common solutions for monitoring printing is the use of a webcam that tracks the process in real time and alerts the operator or halts the print in case an error is detected [11, 12].

Video monitoring of the 3D printing process is an increasingly popular solution due to its simplicity and efficiency. Webcams are relatively inexpensive and can be easily integrated with 3D printers, providing a clear view of the process. These cameras can function in two main ways: active monitoring and image processing.

Active monitoring with automatic error detection allows the user to be informed by a system as a program using image processing algorithms or machine learning techniques to automatically analyse the images captured by the webcam and detect errors in real-time.

Image processing is a key technology for automatic error detection in 3D printing using a webcam [13-16]. By analysing the images captured during printing, an algorithm can compare the current progress with a reference model or a set of predefined conditions to identify deviations or anomalies.

There are two major approaches to image processing for error detection: featured-based analysis and machine learning algorithms.

In feature-based analysis, the approach focuses on detecting specific visual characteristics, such as layer shape, texture, thickness, or colour. If a feature does not match the expected one, the algorithm can detect an error.

A promising area for error detection in 3D printing is the use of machine learning algorithms [17-22]. These can be trained to recognize specific patterns of errors and to make predictions based on images captured by the webcam.

Several types of algorithms can be used for this purpose, such as convolutional neural networks (CNN), which are particularly effective in image analysis. Convolutional Neural Networks (CNN) are a class of deep learning algorithms that have proven to be extremely efficient in image recognition and visual analysis [23-28].

A CNN model can be trained to recognize different types of printing errors, such as nozzle

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clogging, layer shifting, or uneven filament extrusion, by being exposed to a dataset of appropriately labelled images. The process of training a CNN model begins with collecting a large set of images from 3D prints. These images are labelled to indicate the presence or absence of certain types of errors. The model is then trained to recognize patterns associated with these errors. After training, the model can analyse new images in real time and automatically detect errors. Once a convolutional neural network model has been trained and deployed, it can be integrated with the webcam to monitor the 3D printing process in real-time. The algorithm analyses each frame and detects anomalies that could signal the appearance of an error.

There are already several examples of projects and commercial solutions that use webcams and image processing technologies to detect errors in 3D printing. One of the most well-known examples is OctoPrint [29], an open-source platform that allows remote monitoring and control of 3D printers. OctoPrint can be integrated with webcams to provide real-time visual surveillance, and in some cases, it can be configured to stop printing if major errors such as layer shifting or extrusion problems are detected.

Another example is The Spaghetti Detective, [30] a plugin for OctoPrint that uses machine learning to detect printing errors. The term "Spaghetti" refers to a common type of error in 3D printing when the filament begins to tangle and form an uncontrolled mass resembling spaghetti. Spaghetti Detective uses a convolutional neural network [31] to analyse images captured by the webcam and detect such errors. If the algorithm detects an error, it can automatically halt the print and send an alert to the user.

In the future, as image processing technologies and machine learning algorithms become more advanced, we can expect an increase in the efficiency and accuracy of these systems. Additionally, it is likely that we will see their integration into more platforms and commercial solutions, making automatic error detection a standard feature of 3D printers.

Although there are some challenges related to image quality and the complexity of part geometry, these can be addressed by using higher-quality cameras and developing more advanced algorithms. In conclusion, implementing these webcam-based error detection systems has the potential to revolutionize the way 3D printing is performed, contributing to a more efficient, cost-effective, and reliable process.

This study aims to explore the ways in which a webcam can be used for error detection, analyse relevant image processing and machine learning technologies, and provide an overview of the most effective methods for implementing this technology in 3D printing. While this technology has brought many advantages, including design flexibility and the ability to produce complex parts, 3D printing often suffers from errors that can compromise the quality of the final product.

2. Experimental procedure

In Figure 1 it is shown the "spaghetti like" defect on the experimental setup. A webcam is placed on 3D printed in such a way to have the view towards the printer bad.

Fig. 1. *View from the webcam to be recognized*

Although error detection with webcams and image processing algorithms is a promising solution, it is not without challenges. One of the main limitations is image quality. A low-quality webcam may not be able to capture fine details, and under poor or variable lighting conditions, the accuracy of error detection may decrease significantly.

Another challenge is the complexity of printed models. Complex parts with detailed geometries and thin layers may be difficult for image processing algorithms to analyse. In some cases, small differences between the correct part and an error may be hard to detect, especially if the error occurs in less visible areas of the part (Figure 2).

An important aspect of using webcams for error detection is their integration with automated control systems for 3D printers. In this way, detecting an error can trigger automated actions such as stopping the print, adjusting printing parameters, or sending an alert to the user. The webcam constantly captures images, the image processing algorithm analyses them in real-time, and if an error is detected, the 3D printer receives a signal to stop the process. This type

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of automation not only improves the quality of the final products but also contributes to the optimization of time and resources. Using a webcam for error detection in 3D printing is an efficient and accessible solution for improving the quality and reliability of the additive manufacturing process. By utilizing image processing technologies and machine learning algorithms, this system can detect anomalies in real-time, preventing major defects and reducing material waste.

***Fig. 2.**" Spagetti" errors pose variation*

In order to detect such defects, we want to create a custom architecture of DeepLabV3, by changing the number of Dilated Convolutions and the parameterization of the Atrous Spatial Pyramid Pooling (ASPP) module to suit our specific needs. Regarding the dilated convolutions we will change the dilation rates within some convolutional layers in the ResNet backbone to increase/decrease the receptive field. Also related to the ASPP (Atrous Spatial Pyramid Pooling) parameter, we will adjust the dilation rates and the number of convolutional modules in ASPP, to experiment with various levels of detail in capturing the spatial context.

Atrous Spatial Pyramid Pooling (ASPP) is a key component in convolutional neural network architectures used for semantic segmentation, as seen in DeepLab. ASPP is extremely useful for capturing spatial context at multiple scales from an image, allowing the model to understand both local details and global information. Using a customized ASPP brings flexibility depending on the specific application (in your case, detecting filaments in images).

3. Results and discussions

Semantic segmentation is the task of assigning a label to every pixel in an image to identify the objects present, and ASPP plays a crucial role in this process because capturing multi-scale context is of very high importance: Each dilated convolution in ASPP captures information from regions of different sizes in the image. A small dilation rate captures local details (such as edges and contours), while a larger dilation rate captures information from a broader area of the image, which is important for identifying the overall context. Minimizing loss of resolution is a paramount objective when dealing with ASPP as ASPP helps retain image details without losing resolution through excessive pooling, which is essential for capturing small or thin objects (such as the filaments in 3D printing processes). Objects in real-world images can vary in size and shape, and ASPP enhances the model's ability to detect these variations. We developed an architecture that allows a customized ASPP allows for adjusting the dilation rate and the number of convolutional blocks to better fit the characteristics of the data.

In filament detection, a precise segmentation of very thin and irregular objects is needed, and ASPP can be configured to give more attention to fine details by using smaller dilation rates in combination with larger rates to capture the overall context. By using smaller dilation rates for convolutional layers dedicated to local details can avoid losing critical details such as the edges of filaments or fine structures that may be essential for detecting them.

ASPP combines global and local information, which is essential for detecting filaments or small objects within the broader context of the image. This improves the model's accuracy in identifying objects that might be difficult to detect without considering the overall scene context. In the customized architecture we discussed, ASPP was configured with dilation rates of 6, 12, 18, and 24. These values are parameterized to allow for efficient multi-scale feature extraction. Small dilation (6) allows capturing local fine details, such as contours and small textures. In filament detection, this layer would be responsible for precisely identifying the filaments and other thin structures in the image. Medium dilation (12, 18) is ideal for capturing structures at an intermediate scale, such as filaments in the broader context of the printed object. These dilation rates can capture filaments that are spaced apart or span large areas of the image. Large dilation (24) helps capture information from very wide regions of the image and is useful for understanding the overall context. This layer is important for linking locally detected filaments to the general structure of the printed object.

For dilation rate of 6 we obtain 76 % detection rate, for 12 92 % detection rate, for 18 detection rate was 95 % while using 24 dilation rate we obtain only 88 %. The application was developed in Pytorch and it recognized the printing error as shown in Figure 3.

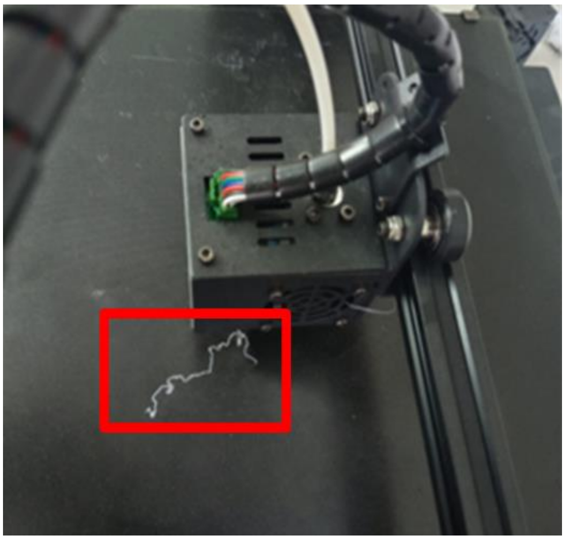

Fig. 3. *Detection of the error*

A well-configured ASPP with variable dilation rates can be crucial for improving performance in applications where detecting small and fine details is critical. Detecting filaments in images, especially in the context of 3D printing images, is a challenging task because filaments have irregular shapes and are often very thin. Smaller dilation rates in ASPP help in the precise segmentation of filaments that are very thin and could be lost in other segmentation approaches that do not use dilated convolutions.

4. Conclusions

Top customized ASPP is a powerful solution for improving the performance of semantic segmentation networks when detecting filaments or other thin and irregular formations.

By using variable dilations and capturing multi-scale context, ASPP allows neural networks to be efficient in capturing fine details and the overall context of the image.

In filament detection for processes such as 3D printing, a customized ASPP can provide a robust solution for accurately segmenting these thin objects and other complex structures, maintaining both local details and global context.

Adjusting the dilations and the number of ASPP blocks can be done to achieve the perfect balance between accuracy and performance, depending on the specific data and purpose of the application.

ASPP extends the receptive field without losing the fine details of the filaments. This allows the network to capture both the local filaments and the general distribution of filaments across the entire scene.

By creating convolutional layers at multiple scales, ASPP helps avoid over fitting on local details. Instead, capturing context at various scales allows the network to detect filaments without over fitting to noise present in the visual data.

Modifying the dilation rate in a customized ASPP can affect the model's ability to detect filaments, particularly depending on their geometry and distribution. ASPP improves the detection of these varied shapes without compromising segmentation precision.

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