Inline image-based reinforcement detection for concrete additive manufacturing processes using a convolutional neural network

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Abstract –

Within the scope of additive manufacturing of structural concrete components, the integration of reinforcement provides an inevitable opportunity to enhance the load bearing capacity of the components. Besides the rebar integration itself, ensuring as-planned concrete cover is key to achieve a stable and long-term legally permissible integration. The thickness of the as-built concrete cover however is unpredictably altered during printing by the varying material behaviour of the printed concrete. In addition, the lack of opportunities to anchor reinforcement elements before printing can lead to a displacement of reinforcement during printing. In this publication, we present an approach for determining the position of reinforcement elements within additively manufactured components without post-process measurement steps. During the printing process, RGB images and depth camera data are recorded by a camera mounted to the print head. Subsequently, a neural network is employed to distinguish between reinforcement structures and the deposited material within the coloured image. By overlaying the colour image data with the depth information a 3D point cloud is generated, within which the reinforcement is marked.

Keywords –

Additive Manufacturing; Process Control; Image Processing; Neural Network; Printing Robot

1 Introduction

In the context of concrete component manufacturing, the integration of reinforcement is essential for the generation of tensile strengths [1]. To achieve comparable loadbearing capabilities with additively manufactured components, reinforcement elements must also be integrated during 3D printing processes [2]. Initial reinforcement strategies for additive manufacturing are presented by Kloft et al. [3]. Aside from the mere integration during the printing process, an additional challenge lies in ensuring and providing proof of accurate positioning of the reinforcement [4]. Evidence is required not only to comply with and fulfil legal guidelines but, also for planning potential post-processing steps and guaranteeing component stability. There are two challenges in providing this evidence. At first, additional process steps should be avoided, so it is advisable to opt for inline data recording during printing. Second, additive manufacturing processes based on concrete generally present a contaminated environment, so robust data acquisition should be emphasized in this case.

In this publication, we present an approach for the fully automatic determination of the reinforcement position within additively manufactured components. Therefore, we record and evaluate image data during two large-scale 3D printing processes with a sensing unit to observe the process and to identify the integrated reinforcement. To distinguish between printed concrete and the integrated reinforcement within the recorded images and data, we propose and prove the applicability of convolutional neural networks (CNN). In section 2, we first describe the state of the art regarding reinforcement integration and detection. Section 3 explains our methodological approach, while section 4 outlines the description of the experimental investigations. Section 5 addresses the results, and section 6 covers the summary and outlook.

2 Related Work

Within this section, we first address the strategies for reinforcement integration during concrete 3D printing processes. This allows us to derive boundary conditions for the data acquisition, e.g. environmental influences such as the degree of air pollution influencing the captured data quality, the required data, and image resolution to detect the reinforcement or the expected colour contrast between material and reinforcement. Afterwards, we evaluate state of art sensing approaches for their suitability and efficiency for the reinforcement determination task during 3D printing processes. Finally, we present research on potential methodological approaches and challenges to evaluate the recorded data.

2.1 Reinforcement Integration and boundary conditions for sensing

According to Pacillo et al., [5], most additive manufacturing processes in construction can be categorized into extrusion-based, binder jetting, or powder bed-based methods. Most of these processes occur without significant dust emission, leaving no special constraints to consider for integrating sensors in most cases. However, Shotcrete 3D Printing (SC3DP), developed at ITE TU Braunschweig [6], belonging to the extrusion-based processes, generates a considerable amount of contamination due to the concrete jetting. This additional challenge prompts us to utilize SC3DP as the most demanding printing process for reinforcement detection. Thus, we aim to develop a sensing approach that works even in such demanding conditions. The process is illustrated exemplarily in Fig. 1.

Figure 1. Shotcrete 3D Printing (SC3DP) at the DBFL of the ITE TU Braunschweig including short reinforcement bar insertion, as proposed by Dörrie et al. [7], and a 2D laser profiler running ahead of the printing nozzle. The goal of our paper is the detection of the depicted type of reinforcement elements.

In addition to the influences arising from the additive manufacturing process itself, the various options for reinforcement integration have different impacts on the to be-chosen measurement approach. Classen et al. [8] provide a brief overview of currently developed reinforcement strategies for additive manufacturing processes. All strategies can be divided according to the usage of flexible reinforcement e.g. textile fibres [9], or stiff reinforcement such as pre-manufactured steel meshes [10], short steel rebar pieces [11] or welding-while-printing utilizing wire-and-arc-additive-manufacturing (WAAM). In all cases, the diameter of an individual reinforcement bar is in the range of a few millimetres, allowing this to be considered as the desired sensor resolution.

2.2 Inline Sensing

For the examination of the position and condition of reinforcement bars within a conventionally cast component, various measurement methods exist [12]. In addition to X-ray imaging [13], for example, ultrasound [14] provides a different approach. These common methods share the commonality that only small areas are captured, and the examinations are carried out on the finished component.

However, in the context of additive manufacturing, there is the option to acquire data during the layer-by-layer construction process, eliminating the need for an additional measurement step. For inline measurement and recording during additive manufacturing processes, generally, three types of sensors are used. Wolfs et al.[15] utilized a 1D time-of-flight sensor to measure the nozzle-to-strand distance while printing. Yet, purely one-dimensional information is insufficient for the detection of (3D) reinforcement elements. An early method for 2D data recording is described by Doumanidis et al. [16], using a line laser and a CCD camera to record 2D profiles of the printed strand. An advanced setting is described by Xiong et al. [17], who use a similar CCD camera aside from a welding setup to generate image data of the process. Lindemann et al. [6] fundamentally transferred such 2D approaches to concrete additive manufacturing. Fig. 2 shows 2D profile data, recorded during SC3DP. The presence of slight elevations within each profile suggests the potential existence of reinforcement structures, see Fig. 1, at these points. However, it is important to note that a definitive identification is not achievable.

More meaningful data can be generated through the use of coloured images and three-dimensional measurements. A 3D data-gathering approach is presented by Kazemian et. al. [18]. The authors utilized a nozzle-mounted camera to surveil a concrete additive manufacturing process gaining 3D images at each layer. The images are evaluated to detect over- or underextrusion for layer width adjustment. Since 3D data, especially in combination with colour images, provides the highest information content for detecting reinforcing elements, we choose a colour and depth camera as the most suitable sensor technology.

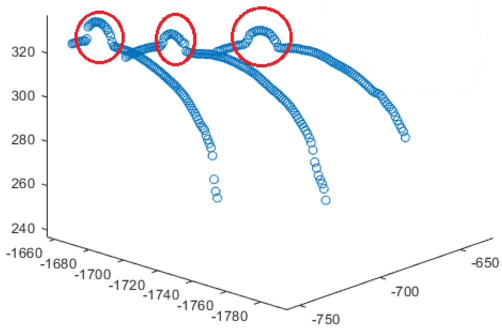

Figure 2. Three 2D profiles recorded during SC3DP at ITE TU Braunschweig. The slight elevations, marked in red in the data, could be part of reinforcing elements, but an explicit identification is not possible.

2.3 Data Evaluation

In the context of data analysis, there are fundamentally two approaches available for image data sets. On the one hand, mathematical methods such as Canny edge detection [19] or thresholding can be implemented. On the other hand, machine learning such as convolutional neural networks is suitable for the examination of image data recorded during additive manufacturing [20]. Previous related work has not yet conclusively shown which method is more effective. We intend to investigate this topic in this work. The following chapter takes a closer look at the individual methods.

3 Methodology

From the state of the art, we derive the necessity to determine the position of reinforcement elements within additively manufactured components. For this purpose, we implement a robust measurement technology which provides meaningful data through colour and depth images. The data is evaluated through mathematical methods and neural networks. The results provide insights into the more suitable approach. Therefore, we have designed a four-stage algorithm, including the following steps:

1. Depth and color image recording by running a camera ahead of the printing process.
2. Identification of rebar pixels within the colored image.
3. Extracting the correlated rebar pixels from the depth image to gain 3D information on rebar positioning.
4. Transforming the depth image into the robot workspace to generate an as-built model. Use a colour contrast to mark rebar elements.

To implement this approach, we first developed a module for the acquisition of inline image data.

3.1 Data acquisition

For inline data acquisition in the context of large-scale additive manufacturing processes based on concrete, we developed a dedicated multi sensor-measuring system. As shown in Fig. 3, this consists of an Intel RealSense D435 for colour and depth image recording. This data is used, as proposed previously, for reinforcement detection. A Raspberry Pi 4 is added to the system for data processing, a Wi-Fi module for data transmission and communication with the printing robot, and batteries ensure the power supply. All of these components are attached to a 2Dlaser profiler. The data of the profiler is utilized in parallel for online control of the printed strand width and height. The whole system runs ahead of the printing nozzle and is rotated by a stepper motor. The 2D-laser profiler and our online strand control approach are described in detail in our previous work [21].

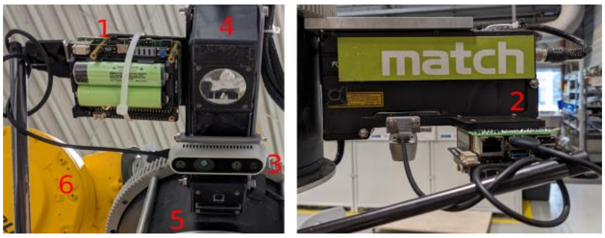

Figure 3. Sensor-module for image processing during 3D printing. 1) power supply 2) Raspberry Pi 4 for data processing 3) Intel RealSense D435 camera 4) Keyence 2D-laser profiler for additional online control 5) Slip ring and gearing for 360° endless rotation 6) printing robot

3.2 Selection of a data processing approach

To compare the two data evaluation approaches, mathematical methods and machine learning, and further develop the more beneficial one in the context of more extensive research, a test image was captured. Fig. 4 shows the test image which contains a printed strand of PU foam.

Figure 4. 3D printed PU-foam strand with inserted short reinforcement bars marked by red circles.

PU foam is used as a substitute material instead of concrete and was already determined to be a suitable substitute for concrete printing process investiagations in previous process-related experiments. Short reinforcement bars (diameter 15mm, length 150mm) were inserted into the foam during printing. The strand dimensions are approximately 10 cm in width and 2 cm in height, closely resembling the concrete-based SC3DP process shown in Fig. 2. Printing and data collection are performed at the additive manufacturing test bench at the Institute of Assembly Technology and Robotics. The test rig is shown in Fig. 5. In this figure, the light colour of the PU-foam is visible. The PU-foam is occasionally darkened during the printing process using spray paint to reduce the colour contrast, resulting in the colour depicted in Fig. 4.

In an initial approach, we attempt to identify the reinforcing elements by detecting circular and angular characteristics using the mathematical method [19]. The first step of identifying the reinforcement bars using the mathematical approach is to detect the edges using Canny Edge Detection. In the second step a Hough transformation is performed, to search for circles and lines. Fig. 6 shows the subsequent algorithms' outputs. As a result, a multitude of arbitrary circles is recognized, making further development seem impractical.

A likewise unpromising result is observed when implementing thresholding methods for edge identification. Depending on the limit settings, either too many or no edges are detected. Consequently, we proceed to use convolutional neural networks (CNN) in further development. In particular, we train and utilize YOLOv8 [22].

4 Experimental data and CNN training

For the CNN training and validation, three different types of images are captured. The types are grouped as

Figure 5. Foam printing test bench at Institute of Assembly Technology and Robotics. 1) printing robot 2) printing head including nozzle and slip ring 3) material supply 4) sensor-module 5) printed column with colouring and rebar integration

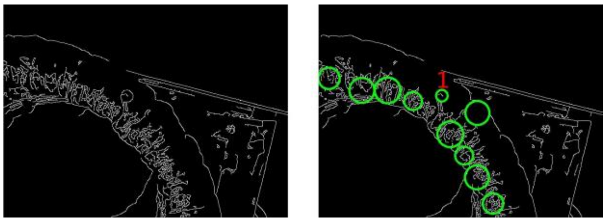

Figure 6. Canny edge detection and Hough transformation applied to a process image of PU-foam printing including short rebar insertion. Only the circle labelled with one correlates to a real rebar.

as follows:

1. sharp: The first set of image data was captured statically above the PU-foam column shown in Fig.
2. blurry: The second set of image data was captured during the printing of the PU-foam column. Due to the printing motion, this data contains motion blur.
3. Concrete: The last set contains image data captured at TU Braunschweig during a Shotcrete 3D printing process as shown in Fig. 1, used for validation only.

The advantage of using statically recorded data, as within the data set "sharp", of existing objects is that no active printing process is needed. Therefore, an arbitrary number of training data can be generated without material wastage. As shown in Fig. 7, motion blur appears during the printing process. Such images are only part of the data set ”blurry”. Two identical YOLOv8 CNNs were trained and validated to determine whether the training set ”sharp” without motion blur is suitable. The training of both networks ran for 150 cycles, each with 640 pre-labelled images. For validation, 59 images were used. Each image set contains 31 images with short reinforcement bars. The validation datasets for both networks include 50% of blurred images, as these occur during the printing process. The detection accuracy of the network trained with blurred data is ultimately 66%. The network without blurred data is close to 0%. Training data without blur is therefore insufficient.

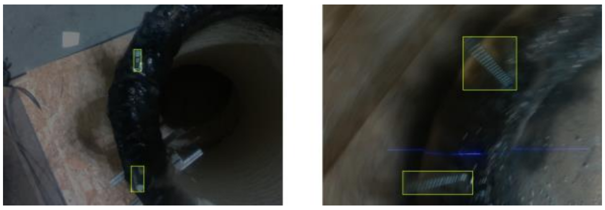

Figure 7. Image recorded with a static robot after printing (left), image recorded during the printing process (right)

5 Results

After training the networks and validating the net trained with blurred data, testing is carried out within the scope of the PU-foam printing processes. Fig. 8 depicts the top layer of a second manufactured column with incorporated reinforcement

Figure 8. Printed and coloured PU-foam column for evaluation. The rebar was added to the last layer and the camera was moved along the printing trajectory over the surface for one full circle. Movement speed was set to 100mm/min

Images were captured and evaluated with a frequency of 0.5 Hz using the trained network on the Raspberry PI 4. After identification of the rebar pixels, labelling is transferred to the depth image, and the depth image is transformed into the robot’s workspace. Fig. 9 shows the assembled and transformed data from all recorded and labelled images.

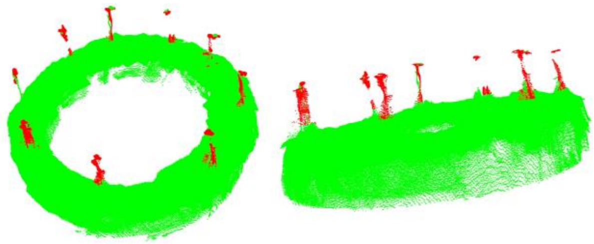

Figure 9. Depth camera data combined to a single point cloud by using the transformation into the robot base coordinate system. Data points identified as rebar are marked in red.

Within the image, the data points recognized as reinforcement are been marked in red colour. It is evident that all reinforcing bars were detected in at least one image, and thus, there exists a portion of red data points for each bar. Furthermore, it can be seen that there are green data points between the red ones, indicating that in some images, the reinforcing bar was not recognized. This correlates with the 66% accuracy achieved in section 4. Such low accuracy, however, is tolerable since multiple images are recorded and evaluated per reinforcement bar. The quantity of available images depends on three factors: the feed rate, the image size, and the data processing speed. In our applications, one reinforcement bar is visible within three images each. With an individual image accuracy of 66%, the overall probability of not recognizing a rod is as low as 4%. After successful identification during the experiments conducted with PU foam, the sensor module was used during the SC3DP. Fig. 10 shows the images marked by the same neural network.

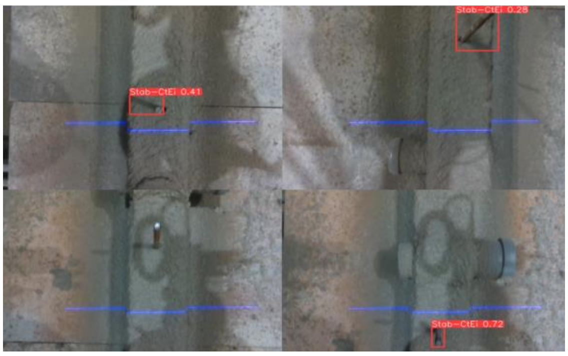

Figure 10. Images recorded during SC3DP evaluated by the trained CNN to label the inserted short rebars.

Basic recognition of the reinforcing bars is possible without training the network with additional data from the concrete process. However, it is evident that the detection accuracy further decreases. This results in clear visible bars (see fig. 10 bottom left) being no longer recognized by the net.

6 Conclusion & Outlook

Inline identification of reinforcement during additive manufacturing processes provides an efficient means to obtain as-built data of a manufactured component without an additional process step. Especially for the verification of, for example, concrete cover or for planning subsequent post-processing, these data provide a solid foundation. In the course of our work, we first developed a module for recording such data. Furthermore, an approach for systematic evaluation was presented, tested and validated in two different production processes. While the presented approach represents a functional methodology for the identification and localization of reinforcement elements during printing, the following basic statements can be derived. Typical for the use of neural networks, and this also applies to the proposed use case, is the relevance of good training data. It turns out that the mere use of post-printing process images is not sufficient to achieve adequate classification during the printing process. The experimental investigations also show that mediocre classification quality can be partially compensated for by high-frequency recording and evaluation of the image data. Such oversampling is limited by the capabilities of the Raspberry Pi 4 in our case. A limitation in the use of the methodology also results from the need for a wireless network for data transmission, which may not always be available for onsite construction. The system is also not yet dust and waterproof in its current state. In the context of future research, we aim to further investigate the accuracy of the recorded data to determine the applicability for the generation of quality inspection documentation. Additionally, we need to evaluate additional network architectures regarding their resulting detection accuracy to improve robustness.

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