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Investigation on semi-virtual dataset based on semantic segmentation for injection molding process monitoring

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Abstract
Image semantic segmentation performed on molds is used to achieve automatic and continuous defect detection during injection molding processing. Generally, a crucial prerequisite for training a robust segmentation neural network is to build a suitable dataset, which requires a large amount of image data with plentiful mold colors, different illumination conditions and specific defect labels. The approach requires long data preparation to collect a sufficient dataset, which could meet the needs of online defect detection during injection molding. To address robust dataset development, the present work uses a 3D CAD modelling software to fabricate defects and colors on molds, creating an augmented mixed dataset with virtual and real-process data. In this investigation, molds printed by vat photopolymerization are used as objects where both the mold images during injection molding process and the virtual mold images from the 3D modelling software are collected. Mixed datasets with different proportions of virtual images are labelled and fed into the segmentation neural network. The experimental work shows that the proposed method provides a reliable dataset augmentation for subsequent IM semantic segmentation frameworks.

Injection molding, Data augmentation, Semantic segmentation, Defect detection

1. Introduction

Injection molding (IM) with additive manufactured molds outperforms conventional fast-prototype approaches [1]. The molds are printed by Vat-Photopolymerization (VPP) [2] and mounted into IM machines within few hours from their conceptualization, which significantly shortens the product development and update cycle . However, photopolymer molds suffer from lower strength and higher distortion during the printing and mounting processes, which makes them more vulnerable when compared with metal molds. Once the mold is broken, the IM process cannot continue before changing a new mold. Semantic segmentation [3] for IM has a potential to detect and segment the breakage automatically, but it requires a robust model due to the randomness and diversity of the occurrence of breakage on a mold. A sufficient IM dataset should consider molds with colors, materials, illumination conditions and different types of breakages. Preparing such a dataset is time-consuming and costly.

The present work proposes a new method for augmenting the IM dataset, where mold images are collected from both the real-world via IM experiments and a 3D modelling software. Semi-virtual datasets are generated and fed into model. The performance is evaluated by comparing the model trained by different proportions of virtual mold images.

2. Methodology

2.1. VPP based molds printing

The real-world molds were produced by a VPP process, illustrated in Figure 1. The CAD file is sliced into several slices along the Z axis. Those slices can be represented as 2-dimension matrices, from where the sliced images can be projected by the UV projector. In each cycle, the building plate moves down, one slice is projected and cured, then the building plate moves up. By repeating this cycle, the mold can be printed on the building plate. It usually takes 40 minutes to print a mold with a thickness of around 2 cm.

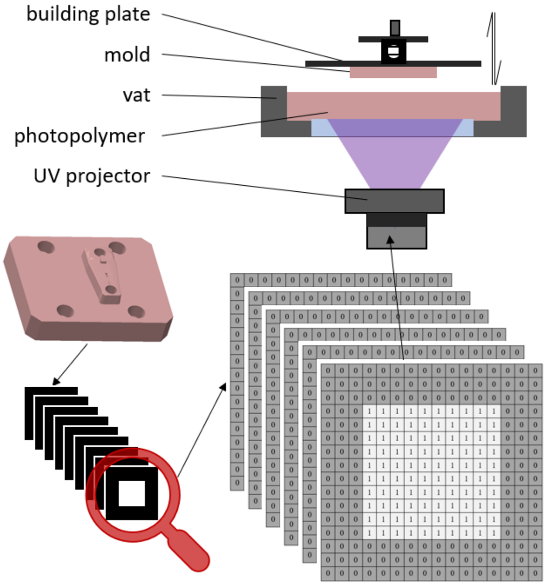

Figure 1. VPP process

2.2. Virtual mold and labelling

Although the VPP process is very fast, it still takes a long time to print and to conduct the IM experiments. To increase the diversity of the dataset, virtual data is produced by a 3D modelling software. The CAD files of the molds are built in Solidworks (Dassault Systems S.A.), where the colors and breakages can easily be edited.

After collecting images of the VPP molds and virtual molds with different colors and breakages, the labels of those images are generated. Each and every pixel in the images is labelled as a class among 'mold', 'breakage' and 'background', as depicted in Figure 2.

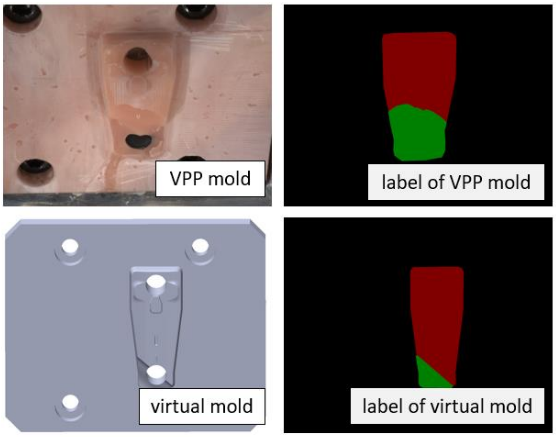

Figure 2. VPP printed mold, virtual mold and labels.

2.3. Semi-virtual datasets generation

Virtual ratio r_v represents the proportion of virtual images in a dataset:

$$r_v = \frac{n_v}{N}$$

where, N is the total number of images in a dataset, n_v is the number of images from the 3D modelling software.

In this investigation, four types of semi-virtual IM datasets are designed with different virtual ratios: 0, 0.25, 0.5 and 0.75. Semantic segmentation models are trained separately based on these four datasets. The Intersection over Union (IoU) [4] of the segmentation results are calculated in order to evaluate the performance.

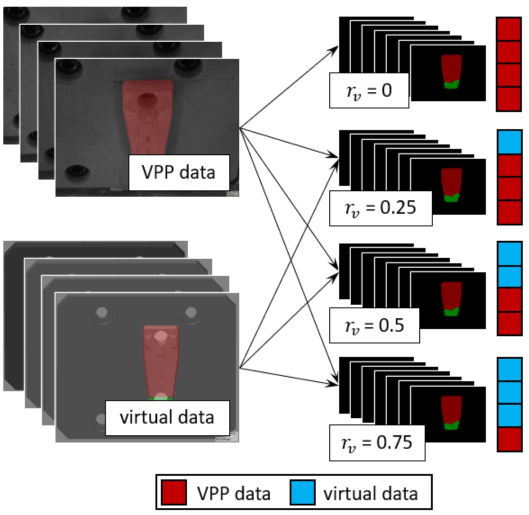

Figure 3. Generation of semi-virtual datasets.

3. Results and analysis

The training is conducted through DeepLab V3 [3] on Nvidia Tesla V100 with 100 epochs each. After the training, the trained model is tested using VPP mold images which are not included in the training set. The results of different virtual ratios are shown in Figure 4.

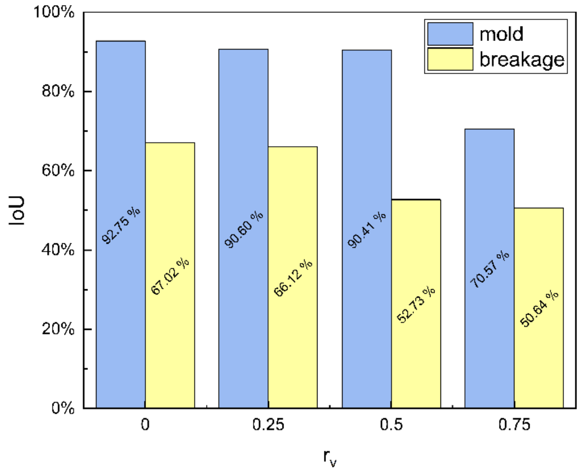

Figure 4. IoU of mold and breakage in different virtual ratios.

It can be noticed that the segmentations of the molds have better IoUs than of the breakages. Considering the datasets, the overall area of the mold is far bigger than of the breakage. In some images before the molds break, there are only mold pixels. This fact explains why the mold class has a better training result than the breakage.

The result shows a drop of IoUs when adding the ratio of the virtual dataset. When the virtual ratio is increased from 0 to 0.25, the IoUs of class 'mold' and 'breakage' decreases to 2.15% and 0.9%, respectively. However, the advantages greatly overweight the drop. By introducing the virtual data, fewer injection molding experiments are needed to collect the varieties of data, thus a large amount of time and costs can be saved. The proposed method has a good cost-performance balance.

4. Conclusion

In the injection molding experiments, especially with additive manufactured molds, there is a high chance of mold breakages. It is hard to predict the locations of the breakage on a newly designed mold. It is extremely difficult to collect a sufficient dataset that contains all the types of breakages by repeating injection molding experiments. The proposed method shows a way to tackle this problem in an industrial setting.

This investigation proposed an economic and fast method for data augmentation for IM semantic segmentation. Changing rendering appearances (colors, materials, illuminations, etc.) takes only seconds in 3D modelling software, which dramatically boosts the efficiency of data augmentation and decreases the cost. In this investigation, several semi-virtual datasets with different virtual ratios are generated and tested. The result shows that in low virtual ratios the proposed method has a great cost-performance balance.

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