Towards Online Structural Validation for Fused Filament Fabrication

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Introduction

Contents

1. Research purpose
2. Prior work
3. Methodology
4. Results
5. Conclusion

Research purpose

Innovation:
No matter which defects are detected for FFF; the final purpose is guaranteeing the printed product quality for real-life utilization. But not all the defects will impact the product quality. So, we want to investigate the printing product structure validation with different defect sizes’ detection by using ML.

Research purpose:
1. In situ defect detection platform.
2. Decision boundary for different defect sizes impacting on product structure validation.
3. Defect size vs. model detection accuracy.
4. Online structural defect detection.
Product quality monitoring

Product structural quality monitoring
- Defect: printing product quality (good/defect)
- Algorithm: SVM, CNN
- Accuracy: 98.2%, 99.5%

Extrusion defect detection

Product bonding quality monitoring
- Defect: good quality, over-extrusion, under-extrusion
- Algorithm: DCNN
- Accuracy: 94%

Infill defect detection

Product infill quality detection
- Defect: infill defects
- Algorithm: naive Bayes classifiers, J48 decision tree
- Accuracy: 85.26%, 95.51%

Process development

Diagram for the experiment methodology.
Defect detection platform and specimen for the FFF printing process
• defect detection platform
• good quality specimen and specimen with defect (1 mm x 1 mm)
• specimen’s dimension

optical camera

dogbone specimen

notch
Data collection

Video for the data collection process.
Deep learning architecture

Designed CNN model structure based on LeNet 5
• 3 convolutional layer
• 3 max pooling layer
• 2 fully connected hidden layer

Designed impactful defects

8 samples for defect 1
Broken at defect: 8
Not at defect: 0

8 samples for defect 2
Broken at defect: 8
Not at defect: 0

8 samples for defect 1
Broken at defect: 8
Not at defect: 0

8 samples for defect 2
Broken at defect: 8
Not at defect: 0
Designed marginal defects

8 samples for defect 1
Broken at defect: 5
Not at defect: 3

8 samples for defect 2
Broken at defect: 8
Not at defect: 0

8 samples for defect 1
Broken at defect: 6
Not at defect: 2

8 samples for defect 2
Broken at defect: 5
Not at defect: 3

8 samples for defect 1
Broken at defect: 0
Not at defect: 8

8 samples for defect 2
Broken at defect: 0
Not at defect: 8
Designed negligible defects

8 samples for defect 1
Broken at defect: 0
Not at defect: 8

8 samples for defect 2
Broken at defect: 0
Not at defect: 8
Defects impact on structural quality

Decision boundary for different defect sizes impacting on structural quality
- algorithm = SVM
- kernel = polynomial
- degree = 3

8 samples for defect 1
- broken at defect: 6
- not at defect: 2
8 samples for defect 2
- broken at defect: 5
- not at defect: 3

8 samples for defect 1
- broken at defect: 6
- not at defect: 2
8 samples for defect 2
- broken at defect: 5
- not at defect: 3
Final defects

Final defect sizes (1 mm x 1 mm, 1 mm x 0.5 mm, 0.5 mm x 0.5 mm) for defect detection accuracy test.
Results: training processes

- training accuracy: 100%
- validation accuracy: 96.11%

- training accuracy: 100%
- validation accuracy: 93.07%

- training accuracy: 99.42%
- validation accuracy: 88.50%
Results: failure prediction

Specimen quality prediction result
• prediction result for good quality with 100% accuracy
• prediction result for failure at location 16 with 99.31% accuracy
Conclusion

1. This paper presented an online methodology of detecting structural defects for FFF.
2. The approach studies defect size vs. model detection accuracy and integrates the product structure validation into the online defect detection rather than just focusing on surface defects.
3. The designed FFF printer integrates an optical camera that can capture the product’s printing process images used to train a CNN model. After training, this method can detect structural defects online.
4. Result shows the proposed defect detection approach has a promising accuracy, even for the minimal structural quality impacting defect size (here is 0.5 mm x 0.5 mm), which is verified to be a feasible method for FFF product defect detection.
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Thanks!

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