Unsupervised Anomaly Detection on metal surfaces after machining

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1. Introduction

Anomaly Detection is a common issue in Computer Vision, including e.g.: detection of defects during quality control in the manufacturing industry. Due to the highly unbalanced datasets (small number of samples with anomalies) and the lack of knowledge of all types of anomalies, the use of supervised learning is often suboptimal. In our research we used Unsupervised Anomaly Detection (UAD) methods, which are based on gaining knowledge during training model on anomaly-free-samples and checking this knowledge through evaluation on samples with and without anomalies, to solve these problems.

2. Problem definition

After the machining process, various defects (examples are presented in Fig. 1) can occur on the surface. Their vision inspection can be very useful for evaluating the machined surface as well as for designing adaptive machining controls. Due to the pre-optimized machining process, the probability of defects is quite low. The proposed methods for defects detection should, based on the learned patterns from anomaly-free samples (correct surface is characterized by periodical traces of the machining tool as presented in Fig. 1), detect samples with anomalies.

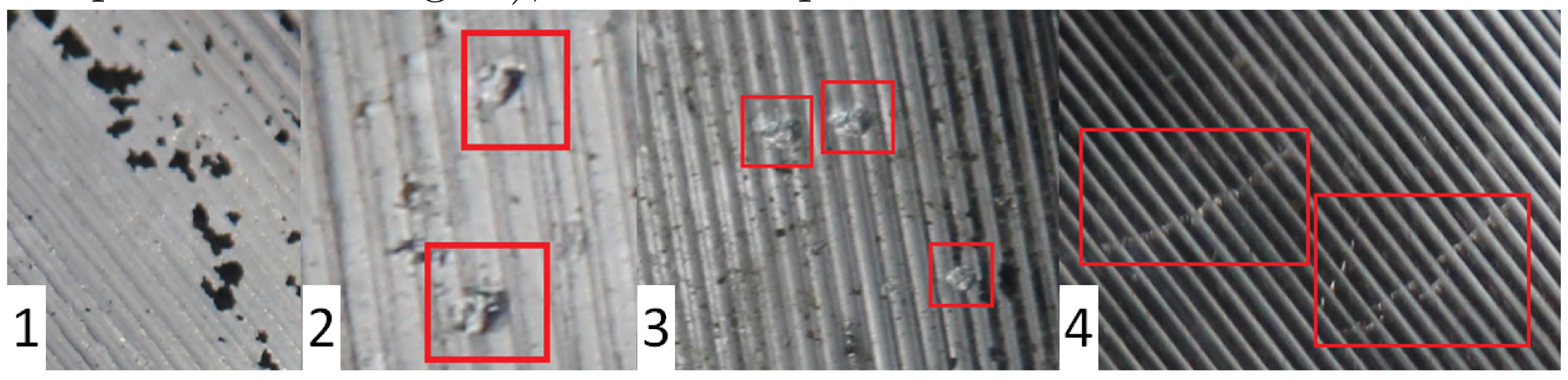

Fig. 1 Examples of surface defects after machining (spalling-1, tear-2, build-up-3, crack-4).

3. Goals

Development of method for defects detection on metal surfaces based on SOTA ML models in unsupervised anomaly detection and localization. Evaluation methods on three different detasets related to our problem:

- Magnetic Tile Dataset (MTD)[4],
- MVTec Anomaly Detection Dataset (MVTec)[5],
- INTOR in-house dataset with anomalies on train wheelsets surface (INTOR).

4. Methods

- **SPADE** (Sub-Image Anomaly Detection with Deep Pyramid Correspondences)[1],
- **Mahalanobis** (Modeling the Distribution of Normal Data in Pre-Trained Deep Features for Anomaly Detection)[2],
- **DifferNet** (Semi-Supervised Defect Detection with Normalizing Flows)[3].

5. Metrics for evaluation

Model Output: anomaly score for whole image (**image level**) or pixels (**pixel level**)

Metric: Area Under ROC Curve (AUC) based on calculated anomaly scores

6.1. Results - image level AUC

	Dataset		
Method	MTD	MVTec	INTOR
SPADE	0.855	0.854	0.918
Mahalanobis	0.937	0.947	0.951
DifferNet	0.964	0.949	0.948

6.2. Results - pixel level AUC

	Dataset		
Method	MTD	MVTec	INTOR
SPADE	0.815	0.964	0.974

6.3. Results - anomaly scores

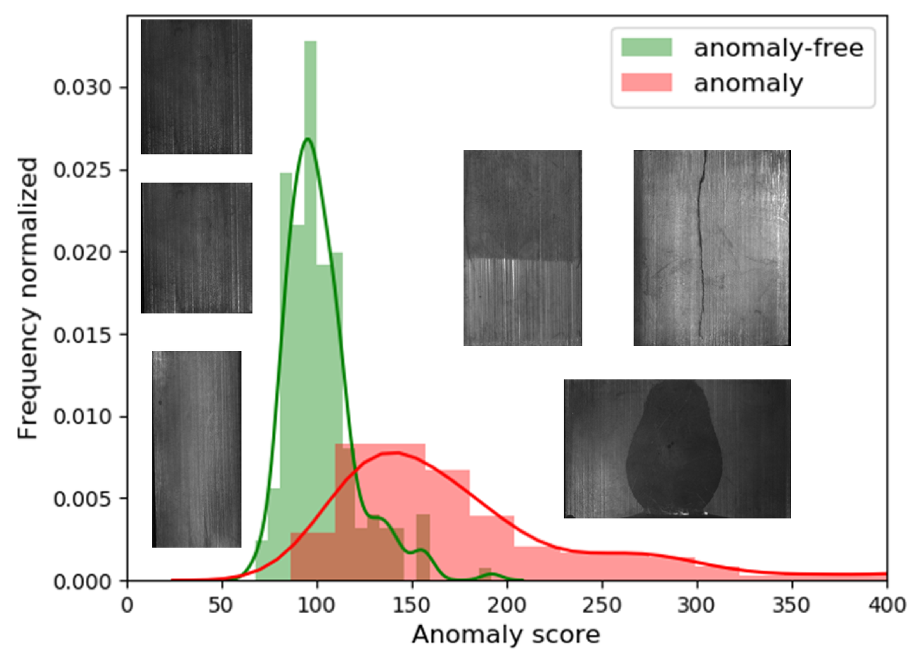

Fig. 2 Distribution of anomaly scores calculated with Mahalanobis.

6.4. Results - pixel segmentation

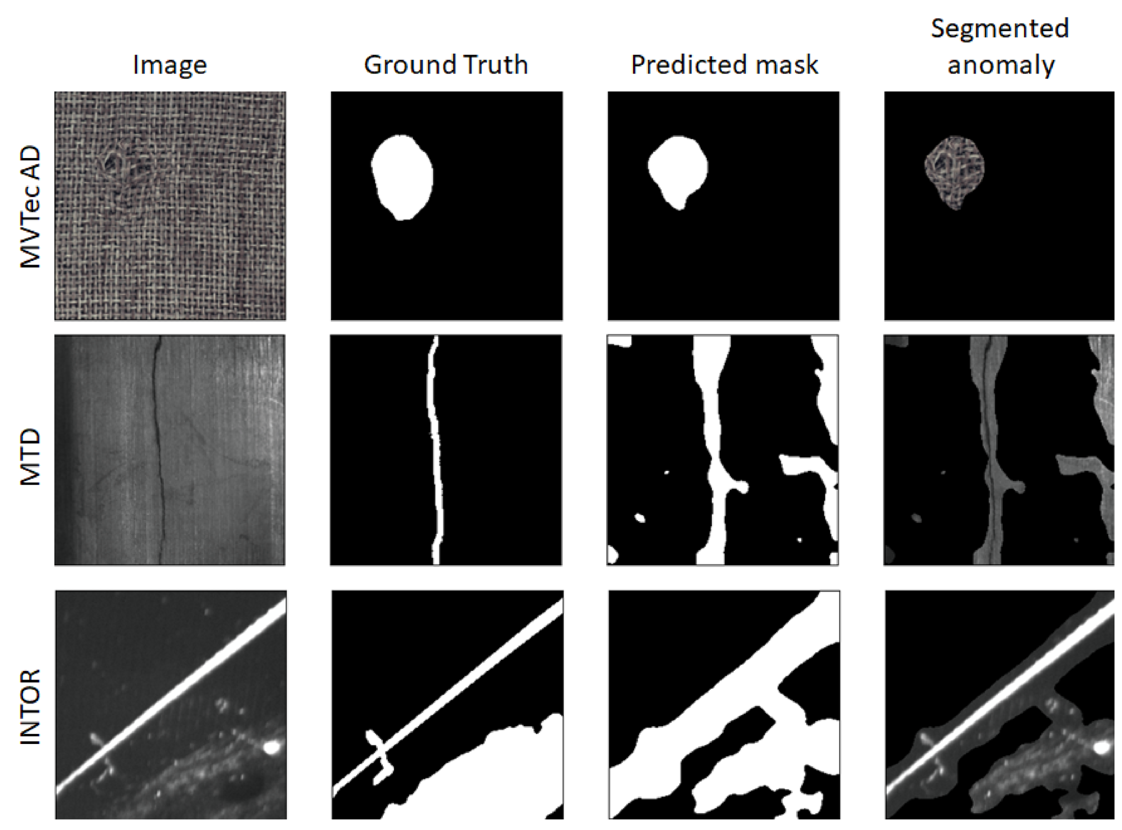

Fig. 3 Examples of anomaly segmentation for samples from different datasets with SPADE.

7. Conclusions

- Our models achieved satisfactory results at image and pixel level on different datasets and can be successfully used to solve problem of anomalies detection on metal surfaces after machining,
- Segmentation of anomalies (Fig. 2) is relatively computationally costly, but increases significantly the level of explainability and comprehensibility of ML models,
- Preliminary assessment of the occurrence of anomalies at the image level (high AUC, low inference time) and subsequent segmentation at the pixel level if anomaly occurs can significantly increase the speed of inference compared to one-stage segmentation,
- Next step in our research will be defects clustering to discover the main types of defects occurring on metal surfaces after machining.

8. References

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9. Acknowledgments

Project **Intelligent precision lathe for regeneration of rail vehicles wheelsets** (POIR.04.01.04-00-0067/17-00) is co-financed from European Union funds under the European Regional Development Funds as part of the Smart Growth Operational Programme 2014-2020.

European Funds Smart Growth
Republic of Poland
The National Centre for Research and Development
European Union European Regional Development Fund