Classifying Defect Types on High-Precision Metal Parts using Semi-Supervised Anomaly Clustering

 $\label{eq:decomposition} \textbf{Degree programme: Master of Science in Engineering}$

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Visual inspection of machined parts requires a high level of concentration but is repetitive and monotonous. Current state-of-the-art solutions to automate this task use anomaly detection, but they only classify parts as defective, not the defect type. A semi-supervised method to predict the type of defect is being developed with Criva AG on a Cendres+Métaux SA use case.

Context

Cendres+Métaux SA (CMSA) is a contract manufacturer of complex titanium medical components. Their products must meet high standards, so a 100% visual inspection is performed by experts. CMSA wants to automate the visual inspection to cope with increased production and to reduce subjectivity. Criva AG's anomaly detection-based software could be a solution. However, this solution does not yet provide the type of anomaly, which is important for manufacturing quality management, as repeated occurrences of similar defects may indicate a production issue.

Motivation

Supervised learning would be the best approach to classify the defects into categories like burrs, dust, scratches, etc. However, it requires a significant number of labeled images. Furthermore, all possible defects must be predefined, since it can only classify defects correctly that are present in the training dataset. Therefore, a semi-supervised method based on anomaly clustering requiring few labeled images is explored.

Implementation

For benchmarking, the clustering algorithm was initially implemented on the popular MVTec dataset to compare it with state-of-the-art methods and to

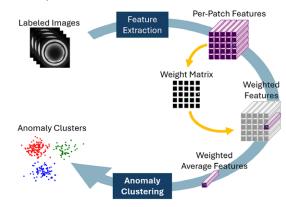


Figure 1: Clustering algorithm

ensure that the extracted features provide enough information to form valid clusters. First, Criva's software is used to extract per-patch features for each image, as shown in Figure 1. These features are processed into weighted average feature vectors. Then, using hierarchical clustering with ward linkage, anomaly clustering can be performed to group similar vectors. This clustering algorithm is then applied to images of CMSA components.

Results and Conclusion

The clustering algorithm achieves similar results compared to state-of-the-art methods on the extracted features of the MVTec dataset. The same approach did not work as well on the CMSA dataset because the images often contain more than one defect type. In addition, the ratio of anomalous pixels to the total number of pixels is smaller than in the MVTec set.

Outlook

To improve performance on CMSA images, clustering should use regions around the defects, as shown in Figure 2. Anomaly detection features can be used to localize defects and create the regions. The proposed solution must be validated using more images of known defects for real-world performance.

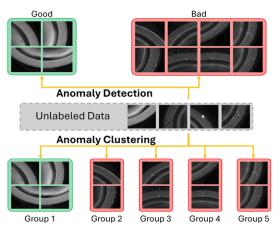


Figure 2: Difference between anomaly detection and clustering



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