Context-Aware Exploration of Image Data (Data Science by A/P Clement Chia)

The project involves developing Image Processing and Automated Visual Inspection (AVI) technologies for Rolls-Royce’s gas turbine systems. Instead of relying on domain experts to detect and categorize surface anomalies, the project investigates features and machine learning techniques for automated anomaly detection/recognition through reliable anomaly identification and classification capability. This project revolves around detecting and classifying two broad categories of anomalies: topographical (surface) and crystallographic (grain deviation).

Anomalies in L-638 C5 Dataset
The C5 subset from AVI L-638 image dataset, consists of four topographic anomalies such as melt, plus metal, scratch and scuff, and one crystallographic anomaly which is shadowing that have sufficient number of labelled examples. Representative examples was used in the analysis for feature extraction, anomaly classification, anomaly detection and incremental learning.

Feature Extraction and Anomaly Classification

Feature extraction is necessary to differentiate anomalies when used as inputs to train/test models for classification and the performance of seven types of feature extraction techniques were analyzed on manually cropped anomaly patches from C5. These include both traditional features such as Scale-Invariant Feature Transform (SIFT), and Convolutional Neural Network (CNN) features. Feature encoding and spatial information were also applied to improve feature representation. After feature extraction, the C5 images are classified into their respective anomaly classes through a classification framework. Popular classification techniques of supervised and unsupervised learning that learns a classification model were explored. In addition to using single features, feature fusion and hierarchical classification were also analyzed. Using the CNN features learnt using a dataset of a different domain through transfer learning along with a linear SVM classifier has shown the most promising results for the manually cut C5 patch dataset. The feature extraction and classification framework is shown in Figure 1.1.1.
Anomaly Detection

Anomaly localization is a crucial step in the automated visual inspection and it facilitates the extraction of patches for anomaly classification. Three methods of Interest Point Detection (A), Template Matching and Interest Point Detection (B) and Phase Fourier Reconstruction (C) were explored for anomaly localization and experiments proved that Method C performed the best in terms of computational time and number of anomalies detected. The overall anomaly detection framework for automated anomaly localization is shown in Figure 1.2.1.

Anomalies in Phase 2 Dataset
Phase 2 dataset captured under an improved viewpoint and lighting sequence was captured along with photometric stereo imaging. A subset of the Phase 2 dataset mainly comprises of six crystallographic anomalies, namely Grains (LAB/MAB/LAB) and Re-crystallized grains (RX/DRX), and scuffing anomalies with sufficient labelled information from an anomaly report. This is used in the analysis to separate grain and non-grain anomalies, and to further classify key grain anomalies.

Capability to Separate Grain and Non-grain anomalies
Visually grain and scuffing can be separated by looking at an image sequence varying in lighting conditions where grain anomalies change in appearance across different lighting conditions unlike scuffing. A technique of resultant difference generates a resultant map based on intensity difference across image subsets to remove constant factors such as background and component design. This emphasizes the behavior of grain and scuffing anomalies and is used as a step in the technique to separate the anomaly types. This change in behavior of grain is shown in Figure 2.1.1.

Figure 1.2.1 Overall Framework for Anomaly Detection

Figure 2.1.1 Resultant Difference Maps with Image Adjustment
Capability to Classify Key Grain Anomalies
A bounding-box based approach to anomaly detection is explored to classify grain anomalies in the Phase 2 Subset. Method C, which was the best detection method in the C5 dataset, is also highly competent in detecting grain and non-grain anomalies from the normal images in this subset. Some examples of applying Method C on normal images is shown in Figure 2.2.1.

![Figure 2.2.1 Anomaly Detection using Method C](image)

The anomaly regions detected and localized through bounding boxes are currently explored together along with feature extraction and classification techniques to classify key anomalies.