An attempt to detect anomalies in car body parts using machine learning algorithms

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Motivation

In order to realize a non-destructive, sustainable and efficient testing process for car body prototypes, we aim at realizing an automated system which is able to both record and evaluate whole sections of car bodies comprehensively and without the need of destroying them. This work provides a first glance of an attempt to automatically detect and characterize possible defects and/or anomalies which occur during common joining processes. We investigated a standard riveting process with respect to the resulting final head height of steel self-piercing half-hollow rivets in aluminium plates (see Figure 1).

Samples & Data

We joined two plates with the aforementioned rivet type who contained either exclusively

- proud head heights (sticks too far out),
- flush head heights (penetrates too deep),
- flawless head height, and
- a mixture of proud, flush and flawless head heights.

The head height is expressed with the parameter $h_r$ (see Figure 2). This physical labelling makes it easier to produce digitally labeled training and test data later on. Only the head height was considered in this work for assessing the joint quality.

The above mentioned joined plates were scanned with both a v|x|tome|x M240 and a v|x|tome|x L240, by GE Sensing & Inspection Technologies. In order to extract only symmetrical mid-sections through the center of mass of the 3D rivet, a principal component analysis (PCA) was used to reduce the dimensionality of the data (see Table 1). For the purpose of the comparison, we used the first three principal components, which together explained $90.8\%$ of the variance. By applying PCA, the mid-sections through the center of mass of the 3D rivet were obtained and the corresponding images were extracted (see Figure 3).

Evaluation Methodology

Four different pre-trained [with 10$^4$ images from the ImageNet data-base [1]] and publicly available CNN architectures were tested with the data set:

- vgg19 with a layer depth of 19 [2],
- resnet18 with a layer depth of 18 [3],
- resnet101 with a layer depth of 101 [3], and
- googlenet with a layer depth of 22 [4].

Partitioning of the data [%]: 60/20/20 (training/validation/testing)

Mini-batch size: 20
Initial learning rate: $10^{-4}$
Epochs: max. 30
$k$-fold cross-validation: $k = 3$ (only subtle changes)

Results

![Table 2: Performance of different networks evaluated with confusion matrices. Top-left: vgg19, Top-right: resnet18 Bottom-left: resnet101, Bottom-right: googlenet. The sum resulting in each column (proud, correct, flush) represent how many instances of each category were actually in the data set. The distribution among the equally named rows, represent the predictions of the network. With an optimally performing network, the red cells contain only zero (no wrong classification) and the green cells the actual value of the category.](image)

Conclusion

We investigated an automatic approach to evaluate the quality of steel self-piercing half-hollow rivets in CT-data. The feature we chose to investigate was the rivets’ head height. The principle feasibility of detecting such a subtle characteristic automatically (even with limited number of samples) was successfully shown. However, in order to increase the network’s reliability and accuracy, the amount of training data needs to be further enlarged and diversified. In order to assess the quality of a rivet joint comprehensively, more quality characteristics need to be considered, meaning more samples need to be produced, scanned and used for training.

References