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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**).

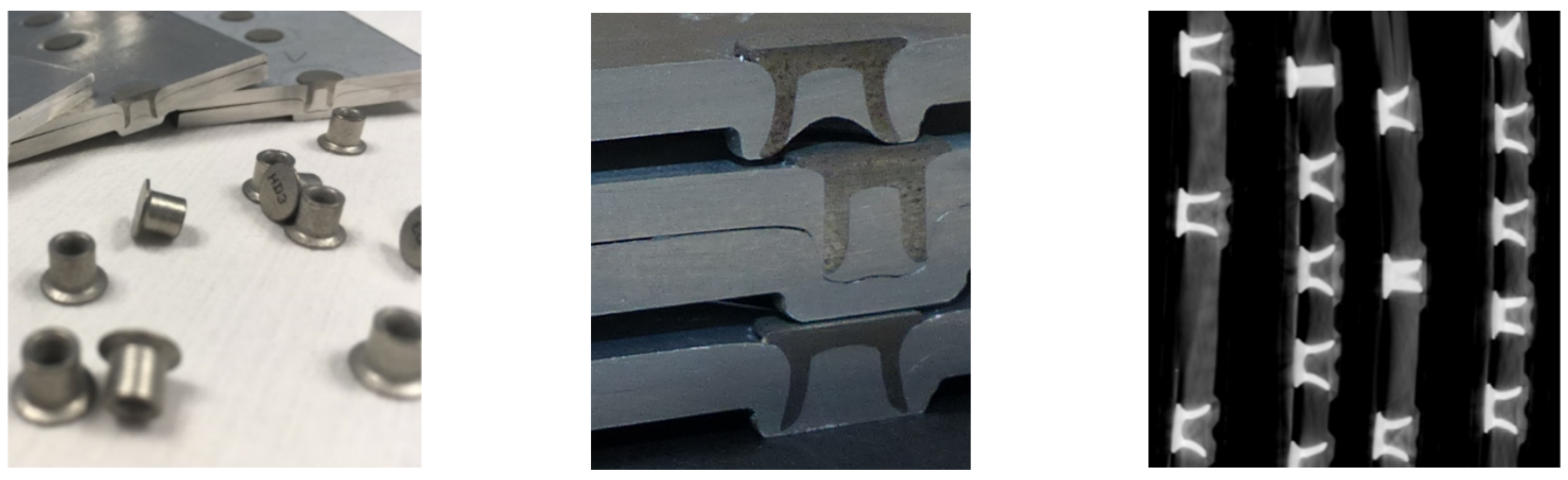

Figure 1: Unprocessed steel self-piercing half-hollow rivets (left), micro sections of rivets processed with different parameters (center), cross section through a CT reconstruction of several processed rivet plates (right).

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.

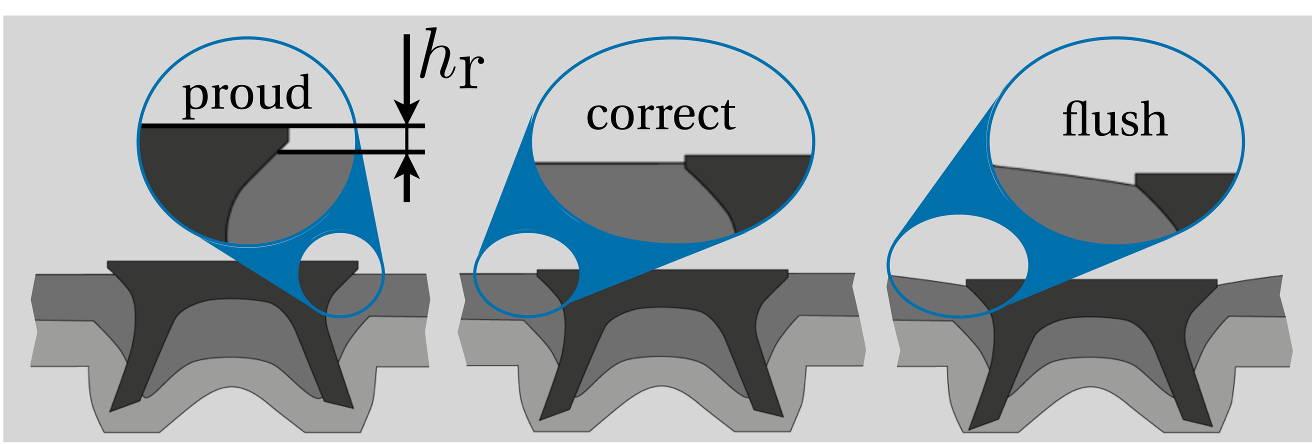

Figure 2: Illustration of the investigated rivet's final head height h_r.

The above mentioned joined plates were scanned with both a v|tome|x M240 and a v|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 employed. Two of the resulting three eigenvectors span the desired mid-sections, that cut the rivets symmetrically in half. To artificially create a larger, more diverse data-set, data augmentation (translation, rotation and scaling) was applied to the reconstructed and extracted rivets (see **Figure 3**). This enlarged the data set by a factor of 6, resulting in 1026 (204 flush, 594 correct and 228 proud head heights) images.

Figure 3: Six examples from both the PCA data set (left) and the augmented PCA data set (right).

Evaluation Methodology

Four different pre-trained (with 10^6 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>
<tr><th></th><th></th><th colspan="4">ACTUAL</th><th colspan="4">ACTUAL</th></tr>
<tr><th></th><th></th><th>proud</th><th>correct</th><th>flush</th><th>Σ [%]</th><th>proud</th><th>correct</th><th>flush</th><th>Σ [%]</th></tr>
<tr><td rowspan="4">PREDICTION</td><td>proud</td><td>45</td><td>0</td><td>0</td><td>100|0</td><td>30</td><td>0</td><td>0</td><td>100|0</td></tr>
<tr><td>correct</td><td>1</td><td>119</td><td>11</td><td>90.8|9.2</td><td>15</td><td>114</td><td>9</td><td>82.6|17.4</td></tr>
<tr><td>flush</td><td>0</td><td>0</td><td>30</td><td>100|0</td><td>1</td><td>5</td><td>32</td><td>84.2|15.8</td></tr>
<tr><td>Σ [%]</td><td>97.8|2.2</td><td>100|0</td><td>73.2|26.8</td><td>94.2|5.8</td><td>65.2|34.8</td><td>95.8|4.2</td><td>78.0|22</td><td>85.4|14.6</td></tr>
<tr><td rowspan="4">PREDICTION</td><td>proud</td><td>33</td><td>7</td><td>0</td><td>82.5|17.5</td><td>43</td><td>2</td><td>1</td><td>93.5|6.5</td></tr>
<tr><td>correct</td><td>13</td><td>105</td><td>13</td><td>80.2|19.8</td><td>3</td><td>108</td><td>7</td><td>91.5|8.5</td></tr>
<tr><td>flush</td><td>0</td><td>7</td><td>28</td><td>80|20</td><td>0</td><td>9</td><td>33</td><td>78.6|21.4</td></tr>
<tr><td>Σ [%]</td><td>71.7|28.3</td><td>88.2|11.8</td><td>68.3|31.7</td><td>80.6|19.4</td><td>93.5|6.5</td><td>90.8|9.2</td><td>80.5|19.5</td><td>89.3|10.7</td></tr>
</table>

Figure 4: Performance of different networks trained with the augmented PCA data set and evaluated with confusion matrices. Top-left: vgg19, Top-right: resnet18 Bottom-left: resnet101, Bottom-right: googlenet.

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 in CT reconstructions by means of image processing and convolutional neural networks 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

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