Diagnostics of welding process based on thermovision images using convolutional neural network

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Abstract. Arc welding used at automated workstations in large-scale production systems requires continuous assessment of welded joints quality. There are known classical methods and diagnostic systems based on the observation of welding current or arc voltage, while along with the development of deep learning methods, the interest in diagnostics by the use of images is increasing. The article presents results of research conducted for the process of joining two stainless steel materials (AISI 304 and AISI 316L) of various thicknesses by means of a fillet weld, aimed at developing a method of diagnosing the welding process using a convolutional neural network. Infrared images recorded using two thermovision cameras mounted on a test stand were used to diagnose the process. EWM Tetrix 351 welding machine operating in TIG technology was used as an executive element. Welds were made at different currents and arc welding voltages, as well as at different welding speeds, which had a direct impact on its quality. The solution for binary classification of welded joints (correct or incorrect) with accuracy above 98% was achieved.

1. Introduction
In the era of digitisation and the fourth industrial revolution (Industry 4.0), there is a possibility to apply modern technology that allows automatization and high repeatability of the production processes, as well as automatic quality control at the manufacturing stage. The advantages of using artificial intelligence at manufacturing plants and Predictive Maintenance strategy were noticed by managers who pay more and more attention to maximizing profit while maintaining or improving the quality of manufactured goods. Advanced supervisory systems should therefore operate in real-time, to diagnose states of the machines, as well as technological processes [1]. In case of machine operation anomalies or process errors, intelligent supervisory system can automatically stop the production process and prevent defective components production [2]. Such systems can be used for various types of processes or machines parts e.g. cold forging [3], imbalance of the CNC spindle [4].

The research presented in this paper describes diagnosis of the welding process using images from thermovision cameras. In the literature research examples in which the welding process was studied using typical time signals [5-8] or thermovision [9-13] can be found. CNN networks are also increasingly used to diagnose the welding process [14-20]. Nevertheless, there is still a need for intensive scientific research to develop process diagnostics methods that exhibit intelligence, robustness and adaptation to disturbances, as well as environment changes. This article is entirely devoted to image-related method and automatic diagnosis of the quality of the welded joint by using a convolutional neural network.
2. Test stand and experiments

2.1. Test stand and parameters of the samples and process
The research test stand (scheme on figure 1) was divided into two sections: executive and measuring. The measurement part consisted of two thermal imaging cameras: Fluke TiS45 and Fluke Ti200, while the executive one was an EWM Tetrix 351 welding machine and a trolley moving in one plane, to which the welding torch was mounted (figure 2).

![Figure 1. Scheme of test stand.](image1)

![Figure 2. Test stand – trolley with welding torch mounted.](image2)

The tests were carried out for the process of joining two stainless steel materials: AISI 304 and AISI 316L with fillet welded joint. The tests were conducted on the basis of experiments carried out for an external company, which made it possible to connect only this type of elements (steel grade, thickness) and only with 60 degree deflexion. Before performing the tests using thermovision cameras, experiments were carried out for various welding parameters. After analysis of non-destructive tests (type of test: VT) results by an external company, optimal parameters for obtaining the correct welded joint were selected. For a well-made seam, the welding current was assumed: 100 A, and the speed of the trolley with the TIG holder: 200 mm/min. These values were modified during the welding process to introduce
anomalies in the process. Other process parameters that were constant for all experiments: argon as a shielding gas with a flow of 10 l/min, tungsten electrode with a diameter of 2.3 mm, chromium-nickel wire, which was fed at a speed of 800 mm/min. Exemplary samples are presented in figure 3, and the basic parameters of the samples are described in table 1.

Table 1. Base samples parameters.

| Parameter                        | Value                                |
|----------------------------------|--------------------------------------|
| Length of the bottom plate (base)| 255 mm                               |
| Length of the upper plate        | 240 mm                               |
| Thickness of the bottom plate (base) | 6 mm (AISI 316L)                     |
| Thickness of the upper plate     | 2 mm (AISI 304)                      |
| Angle of deflexion of plates     | 60° / 120° (from the side of the welded joint) |

Figure 3. View of sample.

2.2. Experiments

In order to ensure uniform measurement conditions, the experiments were conducted according to the following procedure:
1. Marking the sample with a consecutive number
2. Setting the sample in the target place on the test stand ensuring repeatable positioning
3. Setting the position of the welding torch (in 3 axes) at appropriate distances from the sample
4. Starting image recording on both thermal imaging cameras
5. Igniting the arc
6. Starting the trolley move
7. Welding
   • If necessary (e.g. due to curvature of the welded material) correction of the TIG holder adjustment position
   • When performing incorrect samples – change welding parameters (feed speed of the trolley, welding current)
8. Turning off the welding
9. Stopping the trolley
10. Stopping recording images
11. Assessing of welded joint quality by an expert

As a result of the experiments: 18 correct and 15 incorrect samples were obtained (table 2), exemplary samples are shown in figure 4-6.
Table 2. Collection of samples.

| Sample type                                           | Quantity |
|-------------------------------------------------------|----------|
| Correct samples                                       | 18       |
| Incorrect samples (obtained during a process performed with optimal parameters) | 4        |
| Incorrect samples – change of speed of the trolley from 200 mm/s to 100 mm/s | 2        |
| Incorrect samples – change of speed of the trolley from 200 mm/s to 400 mm/s | 4        |
| Incorrect samples – change in welding current from 100 A to 80 A | 3        |
| Incorrect samples – change in welding current from 100 A to 70 A | 2        |

Figure 4. Sample with correct welded joint.

Figure 5. Sample with process anomaly – change of speed of the trolley from 200 mm/s to 100 mm/s (visible overheating of the sample).

Figure 6. Sample with process anomaly – change in welding current from 100 A to 70 A.

3. Classification of the thermovision images

3.1. Data preparation

Even though there are different types of anomalies in the process (related to change of speed, change of current, etc.) the collected image data are split into two classes: correct and incorrect. Welding images were reviewed and labelled manually by an expert considering that only a part of the sample can be incorrect. Based on this information, related thermovision camera pictures were appropriately split to general correct and incorrect classes. This approach provided high quality and reliable data, so the classification model performance is not impacted by improper labels assignment.
For Fluke TiS45 there were 637 samples (images) collected with 2 classes: 190 correct samples like presented in Figure 7, and 447 incorrect samples like presented in Figure 8. Images were stored as BMP images with dimensions: 320 x 240 pixels and bit depth: 32.

**Figure 7.** Example Fluke TiS45 thermovision images of correct welding (images for one sample).

**Figure 8.** Example Fluke TiS45 thermovision images of incorrect welding (images for one sample).

For Fluke Ti200 there were 13 158 samples (images) collected with 2 classes: 7005 correct samples like presented in figure 9, and 6153 incorrect samples like presented in figure 10. Images were stored as BMP images with dimensions: 280 x 210 pixels and bit depth: 24. The difference in the number of images recorded by both cameras was due to the fact that the Fluke TiS45 only recorded images (photos) with an interval every 3 seconds, while the Fluke TiS200 camera as a more extensive model, allowed for recording movies (frames from films were used).
3.2. Convolutional Neural Network architecture
The network architecture showed in figure 12 was proposed for Fluke TiS45 images learning and classification:

- 3 convolution layers, each with parameters:
  - Kernel size 32 x 32 (convolution window size)
  - Strides size 3 x 3 (strides of the convolution)
  - Activation function ReLU (rectified linear unit)
  - Max pooling operation with pool size 2x2 (factors by which to downscale)

- 2 densely-connected NN layers, each with parameters:
  - Dimension 128 units
  - Activation function ReLU

Figure 9. Example Fluke Ti200 thermovision images of correct welding (images for one sample).

Figure 10. Example Fluke Ti200 thermovision images of incorrect welding (images for one sample).
• One dropout operation after last hidden layer output with rate 0.3
• Last (output) layer with Sigmoid activation function
• Adam optimiser algorithm used to control learning rate with Binary Cross Entropy as objective function.

To obtain better classification performance, network structure for Fluke Ti200 (figure 11) has been simplified in comparison to the previous one:

• 2 convolution layers, each with parameters:
  o Kernel size 32 x 32 (convolution window size)
  o Strides size 3 x 3 (strides of the convolution)
  o Activation function ReLU (rectified linear unit)
  o Max pooling operation with pool size 2x2 (factors by which to downscale)

• One densely-connected NN layer with parameters:
  o Dimension 128 units
  o Activation function ReLU

• One dropout operation after last hidden layer output with rate 0.2
• Last (output) layer with Sigmoid activation function
• Stochastic Gradient Descent optimiser algorithm used to control learning rate with Binary Cross Entropy as objective function.

Figure 11. Network architecture graphs for Fluke Ti200. Figure 12. Network architecture graphs for Fluke TiS45
3.3. Classification

Classification model was built with correct samples treated as a negative example (N) and incorrect samples as a positive example (P) as presented in table 2. Accuracy was calculated as Acc=(TP+TN)/(TP+TN+FP+FN)·100%, sensitivity was obtained from the formula: Sen=TP/(TP+FN)·100% and false alarm rate value was defined as FAR=FP/(FP+TN)·100% (TP – true positive, TN – true negative, FP – false positive, FN – false negative).

Network architectures and parameters has been selected empirically. For Fluke TiS45 learning was performed with 100 epochs and it took approximately 16 minutes to reach reasonable accuracy level. Model learning and testing was performed with 10-fold cross validation method (10-FCV). Each fold accuracy per epoch is presented in figure 13. Accuracy for 10-FCV reached by the model was Acc=95.13%, sensitivity equal Sen=97.06%, and false alarm rate FAR=9.23%.

Figure 13. Accuracy for Fluke TiS45 each fold in function of epochs.

For Fluke Ti200 dataset, learning was performed with 100 epochs and it took approximately 4 hours to reach reasonable accuracy level. Model learning and testing was modelled with 10-FCV. Each fold accuracy per epoch is presented in figure 14. Accuracy for 10-FCV reached by the model was Acc=98.59%, sensitivity equal Sen=98.87%, and false alarm rate FAR=1.64%.

Figure 14. Accuracy for Fluke Ti200 each fold in function of epochs.

4. Conclusions

In this paper the classification of fillet welded joint quality between sheets made of AISI 304 and AISI 316L alloys based on images from thermal imaging cameras, using a convolutional neural network was described. The methodology of the conducted research and the results of the binary classification (correct or incorrect welded joint) are presented. Accuracy of classification at the level of 95.13% for images from the Fluke TiS45 camera and 98.59% for images from the Fluke Ti200 camera was achieved. The differences in the accuracy of classification of photos taken by TiS45 and Ti200 are mainly due to the varying number of samples and the different location of the cameras. The obtained results are similar
to other parallel methods described in the literature [14, 15, 18, 19]. Due to the long learning time of the algorithms, for real-time process monitoring tasks it is recommended to prepare and learn networks offline and additional re-train online. High classification accuracy predestines the presented solution for use in quality control systems. Video supervision approach is not new, although it is usually related to review of the product after welding.

The objective of this work is to develop diagnostic method which can be used in the future as an element of the real-time welding supervision system which has been developed in Rzeszów University of Technology (Department of Computer and Control Engineering) [1].

Acknowledgments
This project is financed by the Minister of Science and Higher Education of the Republic of Poland within the “Regional Initiative of Excellence” program for years 2019 – 2022. Project number 027/RID/2018/19, amount granted 11 999 900 PLN.

5. References
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