DOI 10.5162/SMSI2023/D7.2

Arc Welding Process Monitoring Using Neural Networks and Audio Signal Analysis

Saichand Gourishetti[1], Jaydeep Chauhan[1], Sascha Grollmisch[1], Maximilian Rohe[2], Martin Sennewald[2], Dr. Jörg Hildebrand[2], Prof. Jean Pierre Bergmann[2]
[1] Fraunhofer IDMT, Ilmenau, Germany
[2] Technische Universität Ilmenau, Germany
saichand.gourishetti@idmt.fraunhofer.de

Summary:
This paper investigates the potential of airborne sound analysis in the human hearing range for automatic defect classification in the arc welding process. We propose a novel sensor setup using microphones and perform several recording sessions under different process conditions. The proposed quality monitoring method using convolutional neural networks achieves 80.5% accuracy in detecting deviations in the arc welding process. This confirms the suitability of airborne analysis and leaves room for improvement in future work.

Keywords: Deep learning, industrial sound analysis, GMAW, WAAM, DED-Arc

Arc welding Process and Recording Setup

Fig. 1. Illustration of arc welding piece (left) and layer pattern (right).

Additive manufacturing techniques such as arc welding gain importance in the producing industry and quality monitoring plays a vital role in the welding process to ensure the quality of the outcome. Fluctuations in the process parameters such as speed, power, shielding gas rate, and oil contamination can lead to pores in the arc welding seams and thus to poor quality [1]. To generate an appropriate dataset for our analysis, additive-manufactured Aluminium walls with 50 layers were produced. Direct energy deposition was used as the manufacturing process. With a 1.2 mm AlMg4.5 wire, structures were built up layer by layer, as shown in Fig. 1. To prevent exposure of the molten weld pool to atmospheric gases, shielding gas is used. The shielding gas rate was randomly changed for every layer from 15 L/min to 7.5 L/min. Also, oil was randomly applied on the surface of the previous welded layer to simulate the anomalies in the arc welding process.

Layers with 15 L/min shielding gas and with no oil are labeled as *io*. All other layers were labelled as *gasX*, where *X* denotes the rate of shielding gas in L/min. The welds were performed with a Fronius TPS 500i as welding machine and a kuka KR60 as a handling system. Welding speed was fixed to 0.4 m/min. As welding program, the Cold Metal Transfer mix was used with a wire feed rate of 8 m/min and a contact tube to workpiece distance (CTWD) of 12 mm. The produced walls have a length of 150 mm. To ensure a constant sound pressure level the sensors were mounted on a special fixture with a fixed distance to the arc. To reduce the impact of environmental sounds, an acoustic chamber was constructed around the process with molleton as an absorber. The experimental setup can be seen in Fig. 2.

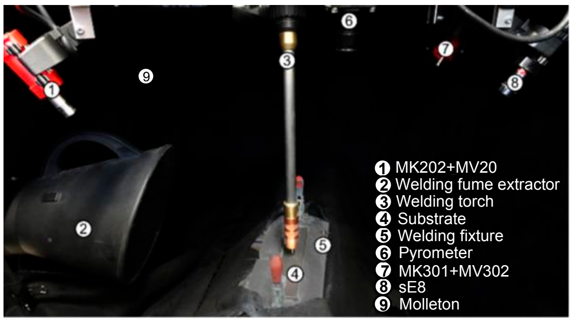

Fig. 2. Experimental setup with microphones and welding equipment.

Dataset Properties

With this recording setup, we produced 11 different wall structures with different arc welding parameters. The number of classes and files per class can be seen in Table 1, and each file is a 15 second long recording of a single welding layer.

DOI 10.5162/SMSI2023/D7.2

Tab. 1: Number of files for each of the different process parameters

io	oil	gas7.5	gas10.5	gas12.0	gas13.5
133	80	64	73	68	70

In this work, we focus on the human hearing range up to 20 kHz for our analysis. To investigate the stability of the recording process, the statistical distribution of the RMS level of the acoustic signals was examined, and no significant difference regarding the process parameters was found.

Neural Network-based pipeline

Based on our previous work [2], we use a convolutional neural network (CNN) for automatic classification. The proposed processing pipeline is shown in Fig. 3. The log power spectrogram is

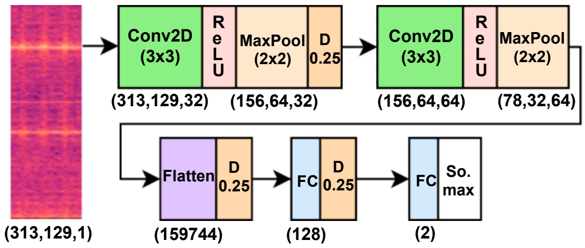

Fig. 3. CNN architecture with 2 convolution layers, rectified linear unit (ReLU) activation, Dropout (D), flatten layer, 2 fully connected (FC) layer, and a final Softmax (So. max) classification layer.

used as a feature representation, computed using the Short-time Fourier transform (STFT) with a window size of 256 and a hop size of 128 samples. The spectrograms are normalized to zero mean and unit variance per frequency bin. Further, we used the mix-up data augmentation technique [3] to improve the robustness of the network. We train the CNN model using the Adam optimizer with a batch size of 16 with categorical cross-entropy loss for 150 epochs and a learning rate of 1e-3.

Experiments and Results

We split the dataset into train and test sets with 5-fold cross-validation and a split ratio of 80% and 20%, respectively. Splits are done on a wall basis to remove any potential biases from the recording sessions itself. In addition, the dataset is balanced by applying the up-sampling technique. First, binary classification is performed, where all *gas* and *oil* classes are considered as *nio*, which results in 80.5% mean file-wise accuracy on the test dataset. Second, we perform a multiclass classification for a more detailed classification where *gas7.5* and *oil* are considered as separate classes. Here, our model yielded a mean file-wise accuracy of 75.4% on the test dataset. The confusion matrices for binary and multiclass classification are shown in Figure 4. One can clearly see which the misclassification between *io* and *nio*. A possible reason for this misclassification could be that the differences in the welding process between *gas* and *io* are too small as compared to *gas7.5*. Furthermore, detailed annotations on anomalies in addition to process parameters and also model hyperparameters tuning could significantly improve the classification results.

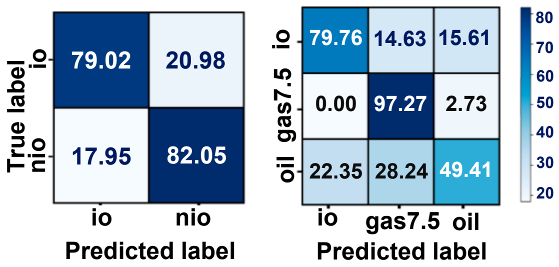

Fig. 4. Confusion matrices for binary (left) and multiclass (right) classification.

Conclusion

In this work, we analyze the potential of analyzing airborne acoustic emissions using artificial neural networks for the arc welding process for quality inspection. Our results demonstrate that acoustic emissions provide useful information for detecting different process parameters which directly influences the arc welding quality. Specifically, this is the case when there is a lack of shielding gas or contamination by oil on the layers. In future work, we want to improve this proposed method by recording more diverse dataset. Furthermore, hyperparameter optimization or better feature representations might improve these results. Also, a more detailed annotation is required to measure when and where pores exactly happened.

References

[1] M. Rohe, B. Stollt, J. Hildebrand, J. Reimann, J. Bergmann. “Detecting Process Anomalies in the GMAW Process by Acoustic Sensing with a Convolutional Neural Network (CNN) for Classification,”. *Journal of Manufacturing and Materials Processing.* 5. 10.3390/jmmp5040135, 2021.

[2] S. Grollmisch, et al., “Plastic Material Classification using Neural Network based Audio Signal Analysis,” in *SMSI*, Nürnberg, 2020.

[3] H. Zhang, M. Cisse, Y. N. Dauphin, & D. Lopez-Paz, “mixup: Beyond empirical risk minimization,” in *ICLR* 2018.

This work has been funded by Federal Ministry for Education and Research (code 01IS20001E (Projekt AkoS). The responsibility for the content of this publication lies with the authors.