Defect monitoring in wire arc additive manufacturing using frequency domain analysis

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Abstract. Efforts to integrate Wire Arc Additive Manufacturing (WAAM) into industrial settings drive a focus on refining in-process defect detection. WAAM commonly employs waveform-controlled welding techniques, like pulsed or controlled dip transfer processes, to enhance material properties and reduce heat input. The cyclic nature of voltage and current waveforms in these processes suggests that valuable information exists in their frequency content for assessing the process state and potential defects. This study introduces the employment of frequency domain analyses, utilizing Fast Fourier transform (FFT) and discrete wavelet transform (DWT) methodologies, to identify anomalies in welding signal data. Statistical assessments reveal the efficacy of online frequency domain analysis in extracting valuable insights across various WAAM processes. The research showcases the utility of this information in developing unsupervised learning techniques for online anomaly detection systems tailored to WAAM, proficient in identifying issues like arc instability, porosity, and geometrical defects caused by arc blow and humping.

1. Introduction

Wire Arc Additive Manufacturing (WAAM) (Fig. 1) utilizes an electric arc to melt wire feedstock, depositing layers to form near net-shape components (Norrish et al., 2021). Although promising for large and intricate metal parts, WAAM faces several defects like porosity, humping, arc blow, spatter, and lack of fusion (Wu et al., 2018). Anomaly detection in WAAM, crucial for defect identification (Reisch et al., 2020), aids in early detection, minimizing defective part production and material waste. Current WAAM anomaly detection tends to rely heavily on supervised learning (Cheepu, 2023; Li et al., 2022; Nele et al., 2022) , demanding a well-labelled dataset. Unsupervised learning, as an alternative, eliminates this complex data labelling (Mattera, Polden, et al., 2023) and can detect anomalies by identifying patterns deviating from the expected behaviour, using solely normal data for training (Chandola et al., 2009; Omar et al., 2013)), thus simplifying the task in an operational industrial setting. While time domain signals offer a degree of information, frequency domain analysis emerges as a valuable tool for extracting a diverse range of information across different frequency bands, particularly crucial due to the close connection between welding waveform frequency content and droplet frequency. The latter, representing the rate of molten metal droplet transfer, is essential for monitoring and controlling welding processes to prevent defects in weld bead geometry and microstructure.

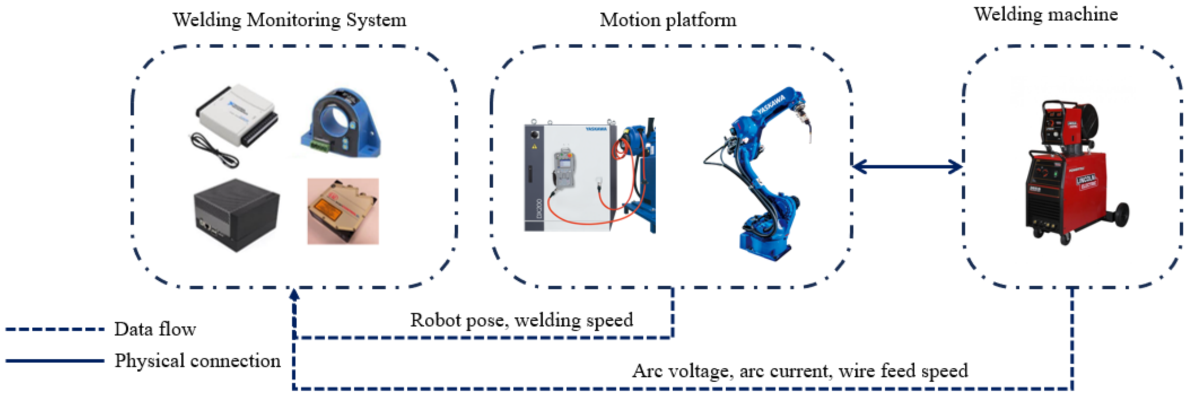

Figure 1: Overview of the WAAM system used in this work. Yaskawa MA2010 motion platform with Lincoln PowerWave S500CE welding power source.

Despite its significance, literature on this subject remains limited and time domain features extraction represent the state of art in this field. Current research (Mattera et al., 2023) predominantly focuses on supervised learning and acoustic emission sensor applications, leaving a notable gap in exploring unsupervised learning within a multi-sensor framework that incorporates current and voltage signals (Ramalho et al., 2022; Zhang et al., 2023). This study introduces a novel method for online anomaly detection in WAAM using unsupervised learning and frequency domain analysis. In this work the frequency characteristics associated with diverse deposition processes, including Pulsed Gas Metal Arc Welding (P-GMAW) and Surface Tension Transfer (STT), across materials such as aluminium 4043 alloy, Inconel 718 alloy, mild steel ER70S6, and stainless steel 316L have been investigated. In particular, frequency analysis techniques like Fast Fourier Transform and Discrete Wavelet Decomposition have been explored to extract features from welding voltage and welding current signals. This study demonstrates the practicality of frequency domain analysis in evaluating WAAM process quality via unsupervised learning techniques for different processes and the applicability for different materials.

2. Frequency domain analysis of welding signals

Frequency domain analysis plays a crucial role in data processing and machine learning, serving purposes such as signal denoising and feature extraction from time series signals. Two widely utilized techniques for this analysis are the fast Fourier transform (FFT) and wavelet analysis. The FFT transforms a waveform from the time domain to the frequency domain, representing the signal in terms of its constituent sine wave frequencies. In contrast, wavelet analysis offers greater flexibility than the FFT. It can analyse signals with complex frequency content using various wavelet functions like Gaussian or Morlet wavelets, enabling analysis at different scales.

2.1 Fast Fourier Transform analysis.

The FFT stands as a powerful tool for signal analysis, facilitating the extraction of a signal's magnitude spectrum. For a welding current signal (Fig. 2), this spectrum unveils the amplitudes of sinusoidal components at different frequencies within the signal. When an intelligent agent learns the magnitudes linked to successful deposition and encounters variations in new data, it may indicate anomalies suggesting potential defects in the process. Statistical analysis of the FFT spectrum provides insights into the energy, frequency peak, and amplitude of the frequency response, enabling differentiation between normal and anomalous behaviour. Traditionally, this method is applied offline, involving the collection of all welding signal samples to construct a comprehensive frequency response at the end of the deposition.

Materials Research Proceedings 41 (2024) 50-59 https://doi.org/10.21741/9781644903131-6

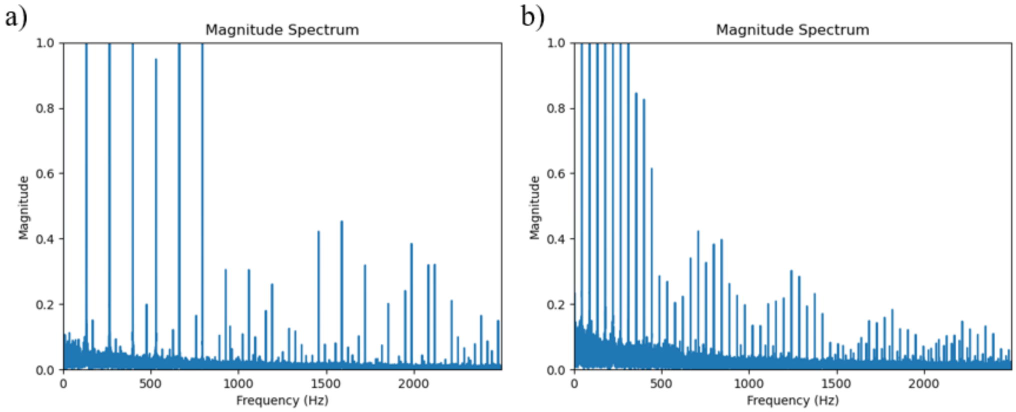

Figure 2: The output of a FFT on a welding current signal for a normal deposition (a) and a deposition with anomalies (b) of a pulsed-GMAW process.

However, due to the lack of temporal information, this approach may struggle to localize defects, and rapid frequency changes associated with defect formation may not be immediately evident in the overall deposition. In such cases, more intricate techniques, like the wavelet transform, can be employed with the same concept but yielding superior results by adapting better and extracting more information from complex signals that vary in frequency response within time.

2.2 Discrete Wavelet Transform analysis.

Although the FFT is applicable for analysing the frequency content of signals, it might not effectively detect minor variations in frequency content, e.g. as it happens when signals display defects. Hence, in cases of varying frequency content in signals, the Discrete Wavelet Transform (DWT) is a more appropriate choice. As showed in Fig. 3, by applying a DWT with a pre-defined wavelet shape, details coefficients of each decomposition may be obtained and features can be derived from them, such as the standard deviation of different decomposition levels, and these features can be used for further analysis.

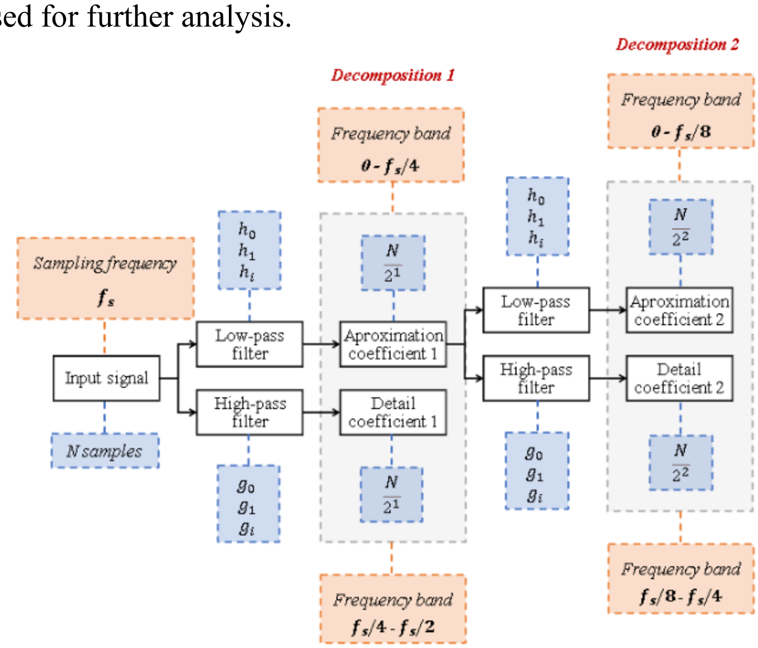

Figure 3: DWT of the input signal allows to decompose it in several detail and approximation coefficients which, as for the results of a FFT, may be used to identify anomalous behaviour.

3. Experiments and Selected Results

3.1. Setup and Data collection

An experimental study was conducted to demonstrate the utility of the presented frequency-based analysis methods to extract features that allow to differentiate normal and anormal behaviour during the deposition process. In these experiments, single-bead walls (100 mm in length), were deposited in a layer-by-layer fashion via the conventional robotic welding system. A number of different consumables were used, each coupled with suitable welding processes and associated parameters, which are outlined in Table 1. Despite multiple layers being deposited during the experimental campaign, this work primarily centres on presenting results by comparing layers deposited under standard operating conditions with layers that displayed defects. These defects encompassed issues such as humping, variations in geometry, porosity and arc instability during the deposition process, as shown in Fig. 4. Two different processes have been analysed in this work. Pulsed GMAW is used for the deposition of Aluminium 4043, Inconel 718 and Stainless steel 316L, while STT is employed for mild-steel ER70S-6. In the P-GMAW process, the power source alternates between high and low currents during each welding cycle. This pulsing action provides better control over the weld pool and reduces heat input, minimizing the risk of overheating and distortion. On other hand, STT is a modified short-circuit transfer process developed by Lincoln that utilizes the surface tension of the molten metal to control the transfer of droplets. Both techniques are employed in WAAM thanks to the lower heat input, which reduce final component’s distortion and residual stress. (Pan et al., 2018)

Table 1: Experimental campaign conducted in this work.

Material	Welding process	WS [mm/min]	WFS [m/min]	CTWD [mm]	Quality Observations
Aluminium 4043	P-GMAW	380	7	12	Normal
		400	7	12	Geometry defect
Inconel 718	P-GMAW	600	8.5	15	Normal
		600	8.5	10	Instability
316L	P-GMAW	750	2	20	Normal
		750	2	20	Humping
ER70S-6	STT	450	4.5	25	Normal
		450	4.5	30	Porosity and instabilities

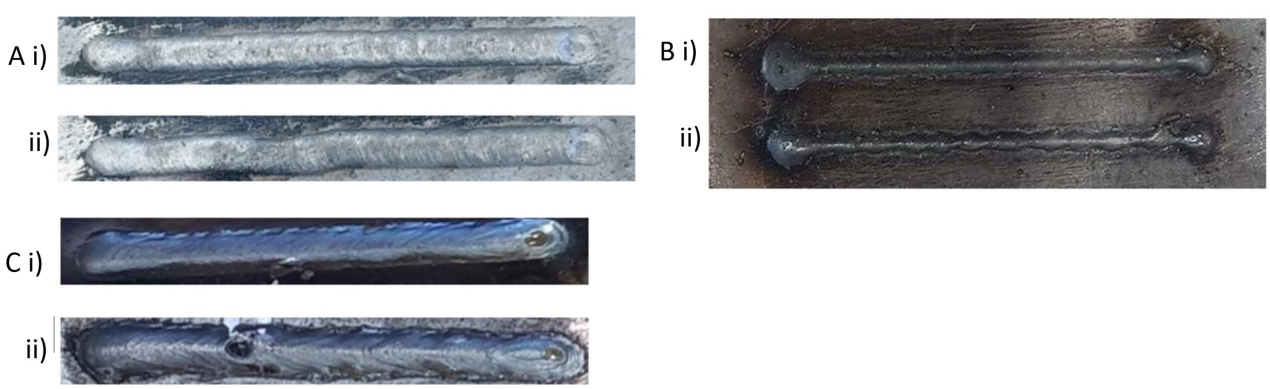

Figure 4: Detected defects. A: 4043 Aluminium i) normal deposition, ii) undesired geometry defect; B: stainless steel 316L i) normal deposition, ii) humping defect; C: ER70S6 steel i) normal deposition, ii) porosity defect.

Materials Research Proceedings 41 (2024) 50-59 https://doi.org/10.21741/9781644903131-6

3.2. Data processing

The gathered data, which includes welding current and welding voltage, was simultaneously recorded, and both spectra were analysed. To develop an online anomaly detection, the data was divided into 1-second intervals, with each interval consisting of 5000 samples due to a sampling frequency of 5kHz. A normalization process was applied to the data. Notably, the maximum and minimum values obtained during the normalization of the normal signal were used to scale the signals of anomalous conditions. From this dataset, 20 features were extracted per second using both FFT and a 3-level DWT with a third-order Gaussian wavelet. Specifically, peak amplitude (PA) and corresponding frequency (PF) were extracted from both voltage and current signals using FFT. Additionally, two features were extracted from each decomposition level in the DWT: Standard Deviation per Level, offering insights into the distribution of wavelet coefficients across various decompositions, and Average Energy of each level, providing a measure of the overall importance of that component in the signal. In total, 20 features were extracted, see Fig. 5.

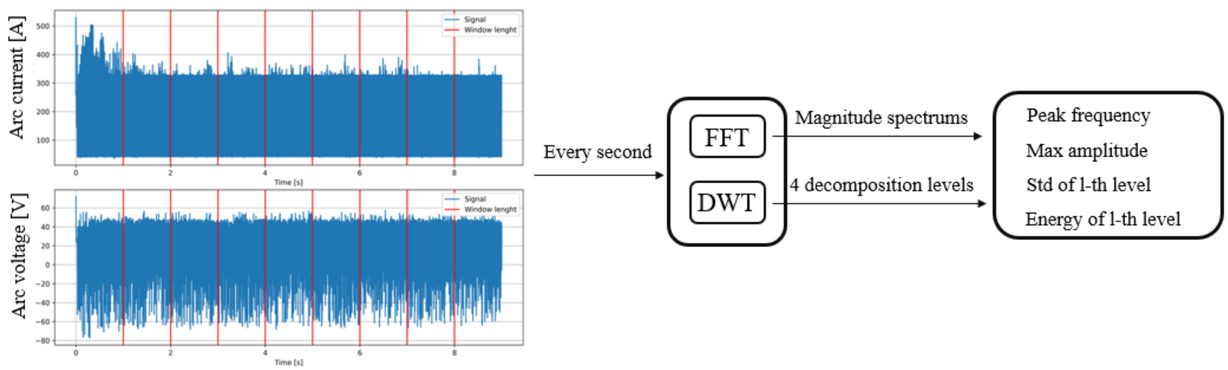

Figure 5: Proposed statistical methodology to extract frequency domain features from welding current and welding voltage signals.

3.3. Results

For visualization purposes, Principal Component Analysis (PCA) was utilized to reduce the dimensionality of normal samples to four principal components. The use of a 3D-scatter plot enables the assessment of the effective discrimination between normal and anomalous data based on the extracted features. Upon observing Figs. 6, 7, 8, and 9, it becomes apparent that the extracted features, represented through their principal components, allow for the division of the feature space. This division facilitates the distinction between portions of the deposition associated with the normal layer (depicted as green spots) and certain portions of the other layer exhibiting defects in some areas. It is evident that by employing a machine learning algorithm, such as the Isolation Forest, the feature space of normal deposition can be learned. Furthermore, using the extracted features from each second of deposition, it becomes possible to detect various types of anomalies in different materials.

Materials Research Proceedings 41 (2024) 50-59 https://doi.org/10.21741/9781644903131-6

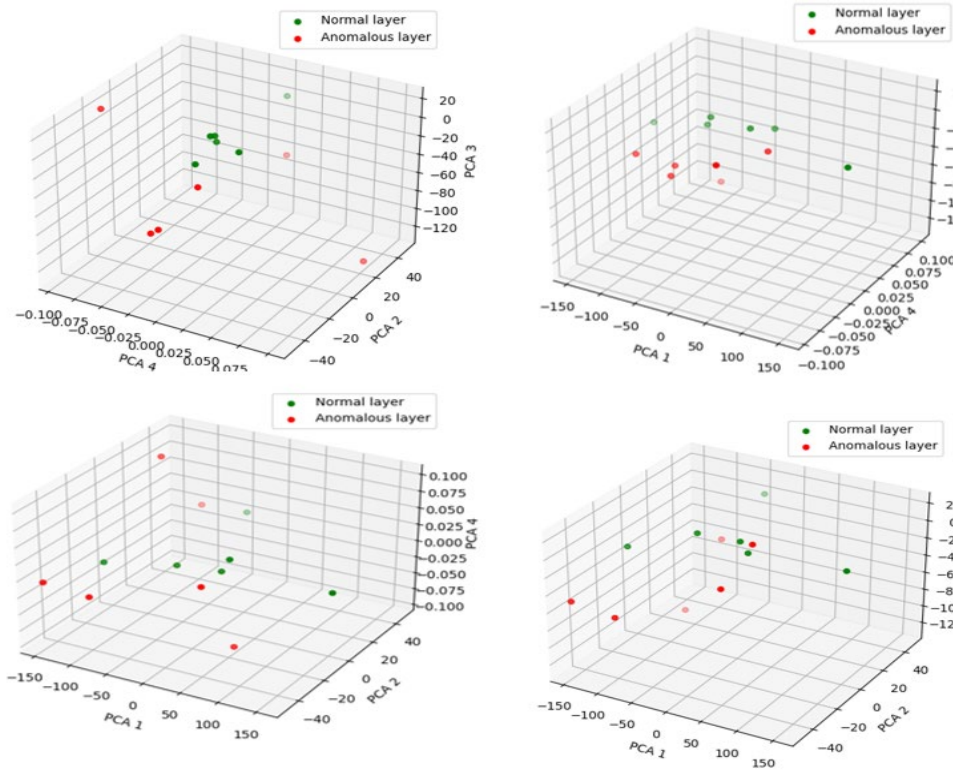

Figure 6: Scatter plots of the 4 principal components which demonstrated that the extracted frequency domain features may be used to distinguish normal deposition from humping in pulsed GMAW of 316L.

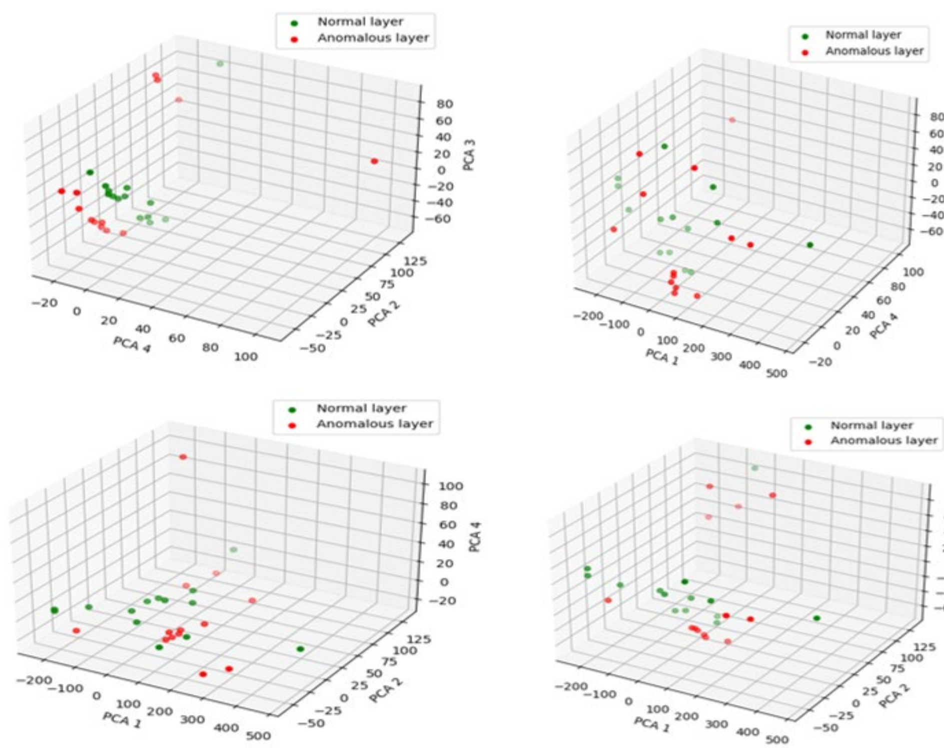

Figure 7: Scatter plots of the 4 principal components of extracted frequency features during a deposition via pulsed GMAW process of aluminium 4043 of a normal layer and a layer subject to a geometry defect due to arc blow.

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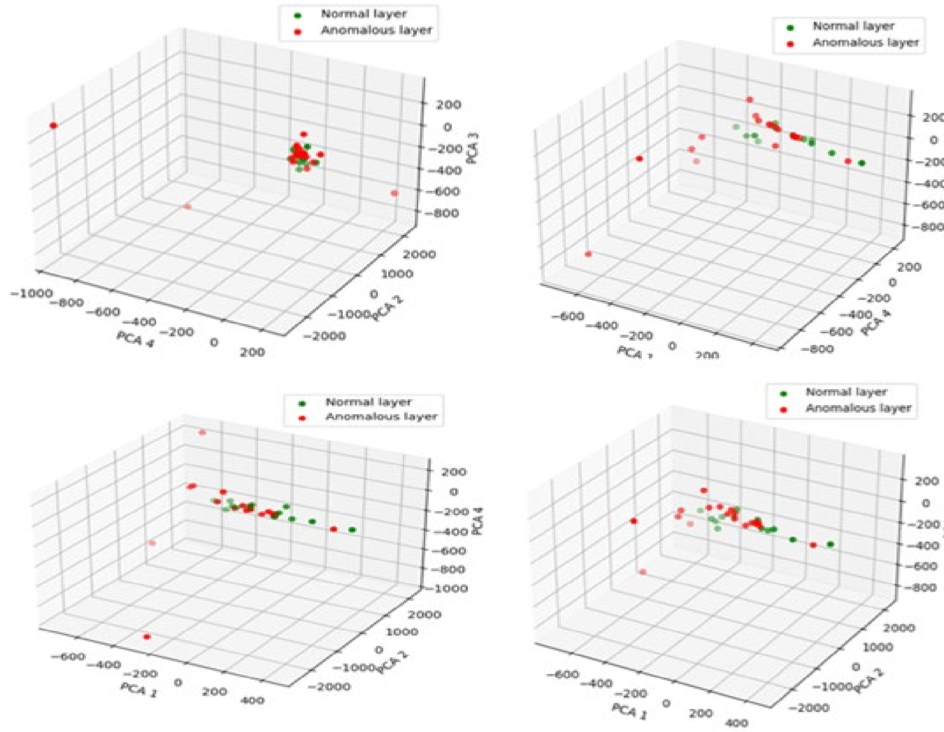

Figure 8: Scatter plots of the 4 principal components of extracted frequency domain features demonstrating that unsupervised learning may be applied to distinguish normal data from anomalous data like spatter in Inconel 825.

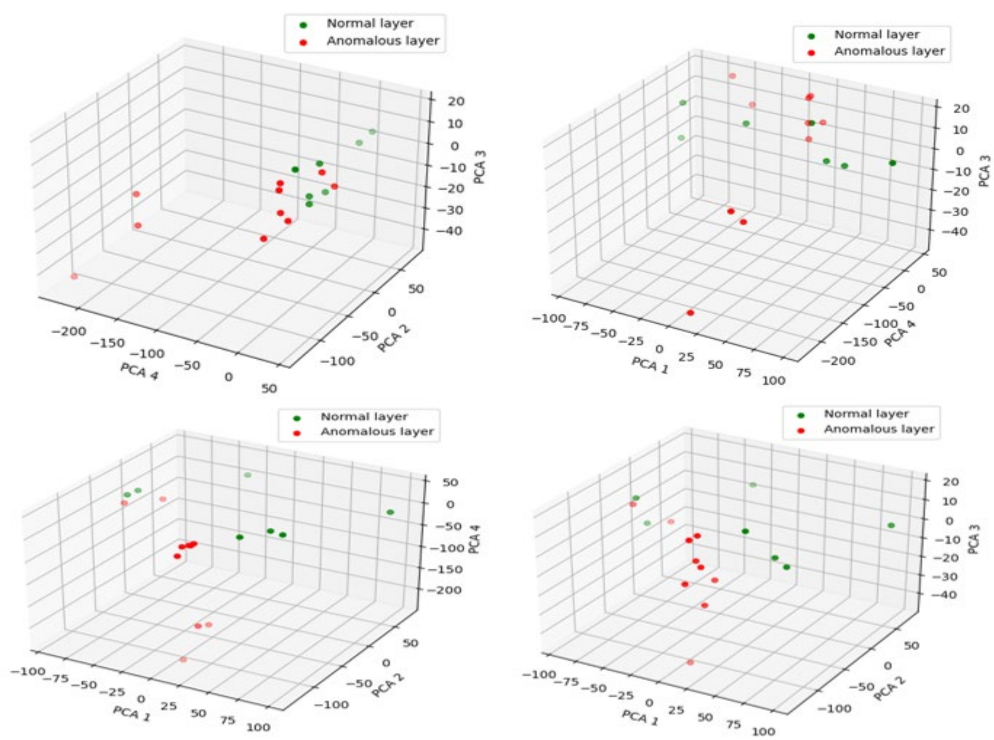

Figure 9: Scatter plots of the 4 principal components of extracted frequency domain features for a normal deposition via Surface Tension Transfer process of ER70S-6 and of a layer presenting defects such as porosity and instabilities.

Materials Research Proceedings 41 (2024) 50-59 https://doi.org/10.21741/9781644903131-6

4. Limitations and future opportunities

The methodology presented in this study utilizes time series and their frequency analysis to identify anomalies. While the scatter plot demonstrates the feasibility of employing this technique for developing an application capable of detecting defects, the manual extraction of features poses a challenge in determining which features are pertinent for distinguishing between a successful deposition and an anomalous one. To address this challenge, a more intuitive and informative approach can be adopted by incorporating additional information through time-frequency analysis. The Continuous Wavelet Transform, for instance, allows the generation of spectrograms that provide insights into the frequency content of different wavelets over time. The wealth of information derived from these analyses can be converted into images and further analyzed using image processing techniques. Numerous features can be extracted using various filters, or automatic features can be obtained through deep learning techniques such as autoencoders. This application of image processing opens up new frontiers for signal analysis, proving to be particularly powerful due to the evident differences between spectrograms associated with normal and anomalous conditions, as illustrated in Figs. 10 and 11 for ER70-6 obtained by STT process and Inconel 718 via P-GMAW. These techniques can be employed not only for online defect detection but also for localizing anomalies in time at the end of the deposition, as time information is present in the final output. Furthermore, an in-depth analysis of the hidden pattern in anomaly clusters can be used to develop semi-supervised classifier.

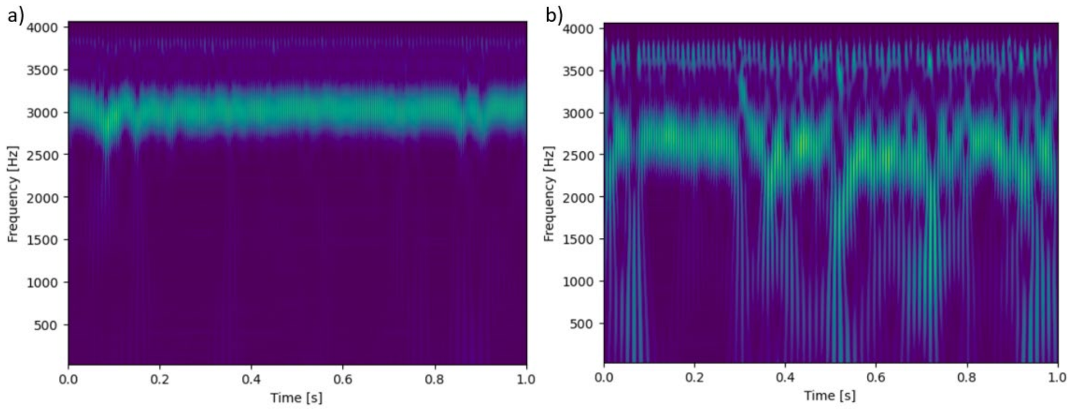

Figure 10: Scalogram obtained from current signal using a Morlet CWT of (a) normal deposition and (b) anomalous deposition with porosity of ER70S6 via STT process.

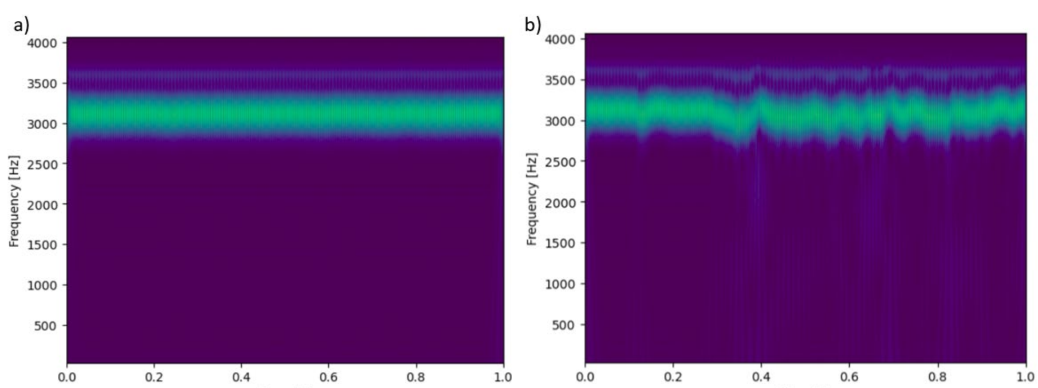

Figure 11: Scalogram obtained from current signal using a Morlet CWT of (a) normal deposition and (b) anomalous deposition with spatter and arc instability of Inconel 825 via pulsed-GMAW process.

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Conclusion

Identifying process anomalies in WAAM applications is crucial for enabling timely intervention in potential repairs. Anomaly detection approaches in this technology area typically rely on supervised machine learning techniques. While supervised techniques exhibit high performance, unsupervised methods offer a reduction of costs related to defect generation and post-processing activities for label generation. However, unsupervised techniques introduce higher uncertainty in output generation, leading to lower performance. This study introduces a method for feature extraction from frequency domain analysis of welding voltage and welding current signals. Utilizing a multi-sensor monitoring system that is less susceptible to external factors, both FFT and DWT are applied for online feature extraction in the frequency domain in different frequency bandwidths. These features, extracted at one-second intervals, proved to effectively distinguish between defect-free and anomalous deposition. The technique successfully identifies defects such as humping, spatter, geometric irregularities due to arc blow, and porosity in materials such as Inconel 825, Aluminium 4043, mild steel ER70S, and stainless steel 316L, showing that this approach can be used for different welding waveform which depends by both process and materials employed. However, limitations associated with manual feature extraction may impact the ultimate performance of the unsupervised algorithm, which serves as the initial layer of a defect detection module in an intelligent production system. To address this, future developments will explore the integration of image processing techniques and a comparison with more advanced time-frequency domain analyses to enhance the anomaly detection capabilities.

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