Infrared Thermographic Evaluation of Cold Sprayed 316L Coatings with Different Heat Treatments

by A. Moskovchenko*, M. Švantner*, M. Vostřák**, Ž. Dlouhá**, Š. Houdková**

* *New Technologies - Research Centre, University of West Bohemia in Pilsen, Pilsen, Czech Republic*

** *Research Centre Řež, Pilsen, Czech Republic*

Abstract

This study evaluates cold-sprayed 316L coatings subjected to different heat treatments (as-sprayed to 1000°C) using infrared thermography. Characterizing these coatings on curved components is challenging due to non-uniform heating and substrate variations. To resolve this, a machine learning framework utilizes features extracted via pulsed phase thermography and principal component analysis. By implementing a hybrid spatial-temporal representation, a Support Vector Machine classifier isolates coating properties from geometric artifacts. The model achieves a 0.98 classification accuracy in multi-substrate training and maintains 0.77 in cross-substrate testing, providing a robust non-destructive method for evaluating cold-sprayed coating states.

1. Introduction

Post-deposition heat treatment can be used to optimize the microstructure and properties of cold-sprayed 316L coatings. Traditional evaluation methods of coating porosity, particle bonding quality, and microstructural homogeneity are destructive and localized [1]. As these properties are also connected with thermal properties of the coating, active infrared thermography (AIRT) offers a non-contact, full-field alternative, utilizing techniques like Pulsed Phase Thermography (PPT), Thermal Signal Reconstruction (TSR) [2], and Principal Component Analysis (PCA) to analyze transient cooling dynamics.

Because of the high pixel-wise variability in transient thermal signal shapes, machine learning (ML) methods offer an efficient tool for analyzing and classifying coatings. They can automate coating classification; however, current ML models face a critical limitation: they rely either on purely pixel-wise signals (ignoring spatial context) or spatial descriptors (losing temporal dynamics) [3]. Furthermore, structural variables, specifically underlying substrate properties and sample curvature, severely compromise model generalization. This work evaluates a Support Vector Machine (SVM) framework utilizing hybrid spatial-temporal feature representations to reliably classify four heat treatment states (as-sprayed to 1000 °C) of 316L coatings. Crucially, model robustness against geometric and material variations is rigorously tested via multi-substrate and strict cross-substrate validation scenarios.

2. Materials and Methods

Cold-sprayed 316L stainless steel coatings with a nominal thickness of 1.5 mm were deposited onto curved pipeline segments. Two distinct underlying substrate materials were used: Steel 11 353 and X52. The coated samples were classified according to post-deposition heat treatment: as-sprayed (no treatment), 600 °C, 800 °C, and 1000 °C. Active pulsed thermography measurements were performed using a mid-wave infrared (MWIR) camera (FLIR A6751, spectral range 3–5 µm) operating at 400 Hz. Thermal excitation was delivered by a high-energy flash pulse, then a sequence of 2000 IR frames was captured during the subsequent transient cooling phase.

To compensate for the non-uniform surface heating caused by the sample curvature, three independent signal transformation techniques were applied to the raw thermal sequences:

- Pulsed Phase Thermography (PPT): Extracting frequency-domain phase spectra via Fast Fourier Transform (FFT), focusing on the highly robust 1–15 Hz range.
- Thermal Signal Reconstruction (TSR): Fitting the logarithmic temperature decay with a polynomial function to compute the stable first derivative.
- Principal Component Analysis (PCA): Reducing temporal dimensionality by projecting the cooling curves onto orthogonal principal components, specifically utilizing odd components (1st, 3rd, 5th).

The optimized feature maps were then partitioned into localized spatial patches to capture context, forming pixel-wise, patch-wise, and hybrid spatial-temporal inputs for a Support Vector Machine (SVM) classifier with a Radial Basis Function (RBF) kernel.

3. Results and Discussion

The classification performance of the SVM model was systematically evaluated under two validation regimes to rigorously test feature robustness against material and environmental variables:

- Multi-substrate scenario: Simultaneous training and testing using mixed pixel/patch data from both Steel 11 353 and X52 substrates.

- Cross-substrate scenario: A strict generalization test where the classifier is trained exclusively on one substrate and evaluated on the other.

Figure 1 illustrates the resulting classification accuracies across all investigated feature representations. The experimental results reveal performance differences between baseline approaches and the proposed hybrid strategy. In the multi-substrate configuration, pure pixel-based features (Phase, TSR, and PCA) yield acceptable accuracies of 0.82–0.85. However, when subjected to the cross-substrate test, their performance drops precipitously to 0.56–0.67. This vulnerability stems from the fact that standalone temporal or phase parameters directly preserve substrate-specific thermal effusivity signatures and local flash excitation non-uniformities caused by the sample curvature.

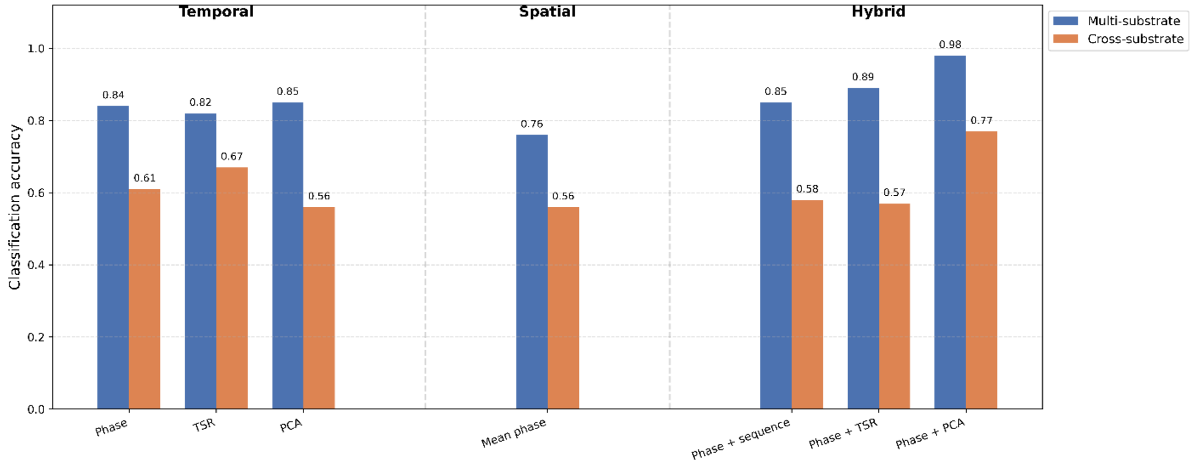

Figure 1. SVM classification accuracy comparison between Multi-substrate and Cross-substrate validation scenarios for different thermographic feature representations

Similarly, the purely spatial approach (Mean Phase) demonstrates poor generalization (accuracy 0.76 and 0.56 for multi-substrate and cross-substrate, respectively), as spatial averaging completely discards the transient cooling dynamics critical for resolving intermediate thermal processing states. In contrast, the Phase + PCA hybrid spatial-temporal representation demonstrates outstanding performance, achieving a classification accuracy of 0.98 in multi-substrate training and maintaining a robust 0.77 in the strict cross-substrate test. This superior generalization is achieved by effectively decoupling the coating's material state from structural artifacts. The local phase patches structurally filter out flash non-uniformities due to implicit phase normalization, while the odd PCA components successfully extract low-dimensional, invariant signatures of the transient thermal decay that are independent of the underlying steel type.

4. Conclusion

This study demonstrates that active infrared thermography coupled with specialized machine learning representations can reliably evaluate and classify the heat treatment states of cold-sprayed 316L coatings on curved components. While traditional pixel- or patch-based processing fails to cross-generalize between different substrate materials due to geometric and thermal artifacts, the proposed hybrid spatial-temporal (Phase + PCA) representation overcomes these limitations. Achieving 0.98 multi-substrate and 0.77 cross-substrate accuracy, this non-destructive approach offers a robust, automated framework for full-field coating quality assurance in practical industrial applications involving complex geometries and variable substrate conditions.

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