CRACK ANGLE ESTIMATION WITH INDUCTION THERMOGRAPHY AND MACHINE LEARNING

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Abstract

Induction thermography is a well-established method for detecting and analysing cracks in metal products, such as rails. However, quantifying defects, particularly those with complex geometries, remains a challenging and intricate task. This paper addresses one critical aspect of defect quantification: the determination of crack inclination angles, which is essential for accurate depth estimation and hazard level assessment. We propose a novel approach that combines induction thermography data analysis with machine learning regression models to estimate crack angles. The regression model is trained on a dataset generated through numerical simulations, ensuring robust and reliable performance. The effectiveness of the proposed method is demonstrated through both numerical and experimental results, showcasing its potential for improving crack characterization in industrial applications. This work advances the field of non-destructive testing by providing a more precise and automated solution for crack inclination angle determination, contributing to enhanced structural integrity assessments.

Keywords: infrared thermography, induction thermography, crack, angle

1. INTRODUCTION

Non-destructive testing (NDT) plays a critical role in ensuring the structural integrity of components across various industries. Among NDT methods, inductive thermography stands out for its ability to detect surface and near-surface cracks in conductive materials by combining electromagnetic induction with infrared imaging. When an alternating current is applied through a coil, eddy currents are induced in the specimen, generating heat. Cracks disrupt these currents, creating thermal anomalies captured by an infrared camera [1].

Unlike optical thermography [2,3], inductive thermography is largely unaffected by surface emissivity variations, as heat is generated internally. Compared to eddy current testing [4], it offers fast, full-field imaging without the need for scanning, although it is limited in detecting deep defects due to the skin effect. These features make inductive thermography a powerful tool for rapid inspection and quality control, especially in metallic structures [5].

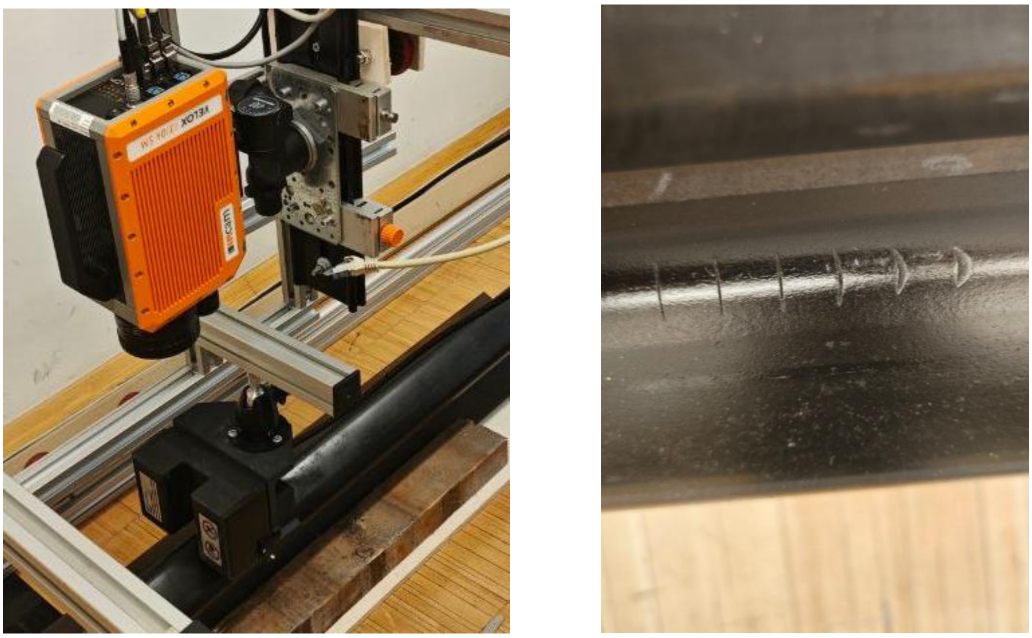
While traditionally used for crack detection, recent advances have shown its potential for characterizing defect geometry [5]. rack inclination angle influences the shape and symmetry of the thermal signature, providing a basis for automated angle estimation. Moreover, knowing the crack angle is essential for assessing crack depth and overall severity. Machine learning (ML) methods are well-suited for this task, enabling robust interpretation of complex, non-linear thermal patterns [6,7]. ML can generalize across various crack configurations and inspection conditions by training on simulated datasets and applying models to experimental data [8,9].

This study presents a machine learning approach for estimating crack angles from thermographic data. Synthetic phase profiles, generated via numerical simulations of induction heating, are used to train the models. Experimental validation is performed on metallic specimens with artificial cracks. The proposed method offers a reliable framework for enhancing defect characterization in inductive thermography through automated angle estimation.

2. NUMERICAL SIMULATION AND EXPERIMENTAL SETUP

Three-dimensional finite-element simulations in ANSYS Multiphysics generated the synthetic thermographic data for angle estimation. Models captured eddy-current distributions and resulting Joule heating around surface cracks, producing time-resolved temperature maps that simulate the thermal signatures recorded in inductive thermography experiments.

The experimental setup for inductive thermography comprised an induction generator with an air-cooled, U-shaped inductor (10 mm wide, ferritic core, copper windings), an infrared camera, and a test specimen. The inductor operated at 30 kHz with a 50 ms pulse. Thermographic data were recorded using an IRCam VELOX 1310k SM camera with a cooled Indium Antimonide (InSb) detector. The camera provided a 180 Hz frame rate at 1280 × 1024-pixel resolution and a 1.5–5.5 μm spectral range. The specimen, a 1000 mm × 50 mm × 30 mm section of a railway rail, featured artificial cracks on its rounded head. Crack parameters included perpendicular cracks at depths of 0.5, 0.75, 1.0, 1.25, 1.5, 1.75, and 2.0 mm, and 1.0 mm deep cracks at inclination angles of 0°, 15°, 30°, 45°, 60°, and 75°, with depth measured normal to the surface. Thermographic sequences were recorded and processed using Matlab software. **Figure 1** shows photo of the experimental setup and the sample of a rail piece with artificial cracks made at different inclination angles.



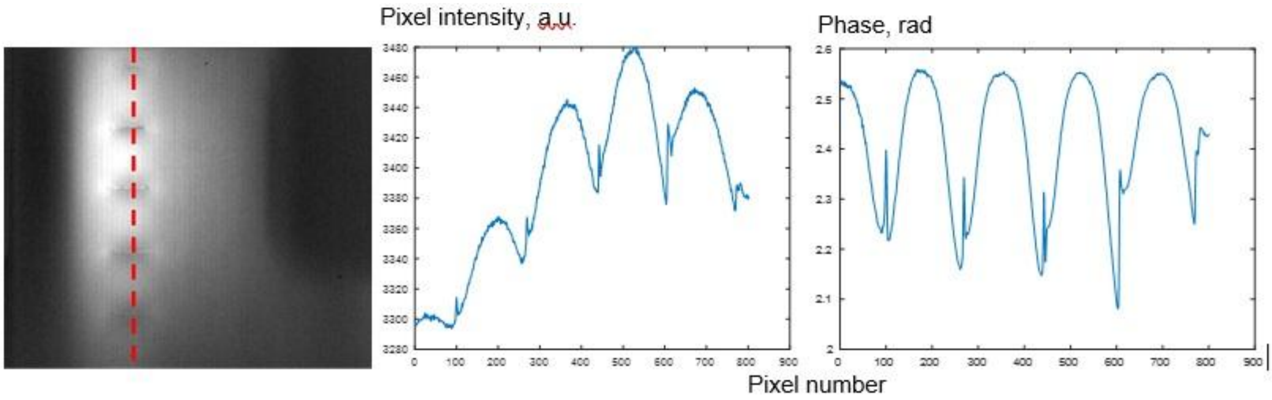
a) b)

Figure 1 Photo of experimental setup (a) and sample (b)

3. METHODOLOGY

The results of the infrared thermographic inspection yielded a sequence of thermograms capturing the transient thermal response of the coatings following flash heating. Inductive thermography produces time-resolved infrared (IR) image sequences that capture surface temperature variations caused by eddy current-induced heating. To enhance defect visibility, suppress noise and non-uniform heating effect, the Fast Fourier

A fast Fourier transform was applied to each thermal sequence, yielding corresponding amplitude and phase image sequences. The first phase image, corresponding to the dominant excitation frequency, is used as the primary contrast-enhanced thermogram [10]. **Figure 2a** shows a representative thermogram of the rail specimen; **Figure 2b** plots the temperature profile, and **Figure 2c** presents the 1D phase profiles extracted perpendicular to the cracks (marked in red in Figure 2a).



a) b) c)

Figure 2 Example of the thermogram of the rail piece sample (a), temperature profile (b) and phase profile (c) perpendicular to cracks

A one-dimensional phase profile was extracted perpendicular to the crack at its centre for each detected crack. A 3 × 3 - pixel median filter was applied to these profiles to reduce local noise. The resulting smoothed phase profiles served as input vectors for machine learning (ML) models, encoding geometric information pertinent to crack orientation.

Regression models were developed to estimate crack angles from the processed phase profiles. Using MATLAB's Regression Learner tool, various algorithms were trained and evaluated, including regression trees, support vector machines (SVM), Gaussian process regression (GPR), bagged trees ensembles, and three-layer neural network.

The training dataset comprised synthetic phase profiles generated through numerical simulations for crack depths of 0.5, 1, and 2 mm. To assess model performance on unseen data, a simulation-based test dataset included additional depths of 1.5 and 1.75 mm. Each crack was represented by multiple profiles, including the central profile and additional profiles offset along and perpendicular to the crack length, to account for potential positional inaccuracies in real-world scenarios. To simulate experimental variability and enhance model robustness, multiplicative noise with a 2 % standard deviation was introduced to both training and test datasets.

Figure 3 shows processed input vectors (FFT phase profiles with median filtering) for both simulated and experimental data of a 30° crack.

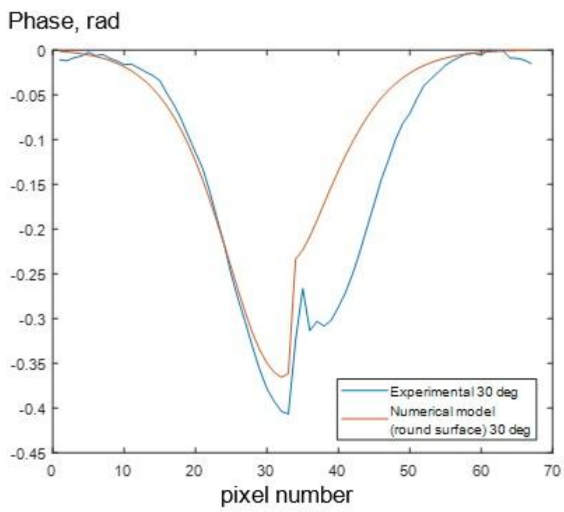


Figure 3 Examples of the simulated and experimental phase profiles used as input for ML models

Model performance was measured by root-mean-square error (RMSE), which reflects the average deviation between predicted and true angles (in degrees). **Table 2** compares validation-RMSE for five MATLAB Regression Learner models: regression tree, SVM, Gaussian process regression (GPR), bagged-trees ensemble, and a three-layer neural network, using 5-fold cross-validation. An independent simulated test set (with added noise) then assessed generalizability.

Table 2 Comparison of ML models

ML model	Regression tree	SVM	GPR	Bagged trees ensemble	Neural network
RMSE, °	5.8	8.4	2.6	5.0	3.4

GPR model achieved the best performance with RMSE = 2.6° on validation dataset and reached 4.3° RMSE on the noisy test data. **Figure 4** presents a residuals box plot for the test dataset, illustrating the distribution of prediction errors in crack angle estimation. In this plot, residuals (differences between predicted and actual angles) are summarized to assess model accuracy. A box plot displays the median, interquartile range, and potential outliers, providing insights into the variability and central tendency of the residuals. A narrow interquartile range and minimal outliers suggest that the model's predictions are consistently close to the actual values, confirming its effectiveness in estimating crack inclination angles.

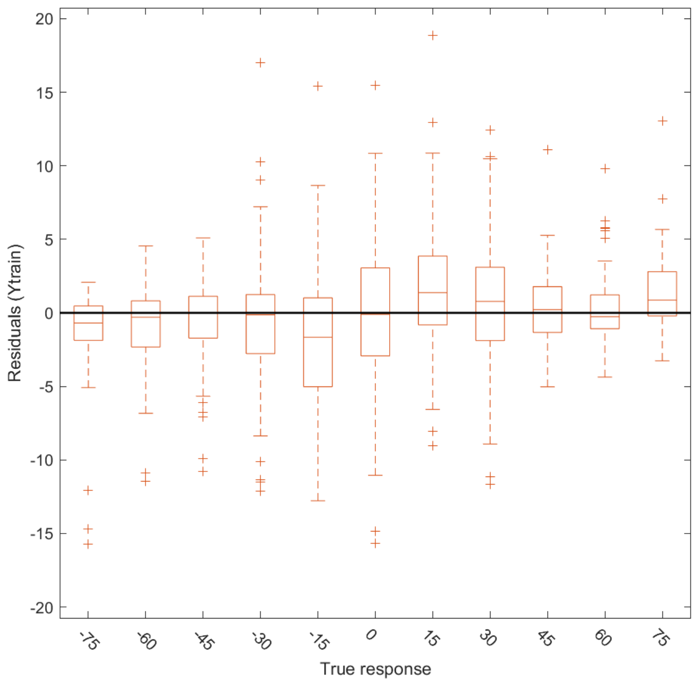


Figure 4 Residuals box plot for the GPR model using the simulated test dataset

The performance of the machine learning model declined when applied to experimental data, with the RMSE increasing from 4.3° on simulated data to 14.2°, particularly underestimating inclination angles above 15°. This discrepancy likely arises from factors such as imperfections in artificial crack fabrication, differences between the numerical model and actual material properties, and the influence of noise and external variables on experimental results. Despite this, the model effectively estimated low inclination angles and remained responsive to angle variations, albeit with a consistent underestimation. Generally, models trained solely on simulated data may not perform optimally under real experimental conditions. Therefore, this performance, while not perfect, is promising. To improve accuracy, future work could incorporate experimental data into the training set or refine models to better reflect real-world material properties and noise characteristics.

4. CONCLUSION

This study demonstrates the feasibility of estimating crack inclination angles in metallic components using inductive thermography combined with machine learning. By applying fast Fourier transform (FFT) to thermal image sequences, phase images were generated, from which one-dimensional phase profiles perpendicular to cracks were extracted and smoothed. These profiles served as input features for various regression models trained on synthetic data.

Among the evaluated models, Gaussian Process Regression (GPR) achieved the best performance, with a root mean square error (RMSE) of 2.6° on validation data and 4.3° on simulated test data. However, when applied to experimental data, the RMSE increased to 14.2°, particularly underestimating angles above 15°. This discrepancy likely results from differences between simulated and real-world conditions, including material properties and noise factors.

Despite these challenges, the model effectively estimated low inclination angles and remained sensitive to angle variations. To enhance accuracy, future work could incorporate experimental data into the training set or refine models to better reflect real-world conditions. Overall, this approach shows promise for non-contact, rapid assessment of crack orientation, contributing to improved structural health monitoring and maintenance strategies.

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