Anomalous Weld Identification by Applying Principal Component Analysis to Magnetic Flux Density Data Captured by a Free-Floating ILI Tool

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Abstract

Free floating inline inspection (ILI) tools using magnetic flux density (MFD) measurements have been enhancing pipeline integrity programs for nearly a decade. The use of MFD measurements to infer information on the pipeline wall condition has been demonstrated and with more inspection data becoming available, the capability of using MFD measurements is continuously increasing. This work focuses on anomalous weld identification by applying principal component analysis to magnetic flux density data captured by free-floating ILI tools. The concept of principal component analysis will be explained, how this approach can be applied to unsupervised classification tasks in general, and the results of the specific use case of anomalous weld identification.

Introduction

The global demand for hydrocarbons continues to grow, placing increased pressure on pipeline infrastructure. Pipelines serve as the primary mode of transport for oil and gas, spanning continents and oceans to deliver energy to consumers. Despite their efficiency, pipelines are susceptible to failures, which can have far-reaching consequences. For example, in 2016 in North America a pipeline failure resulted in the release of 2,000 metric tons of hydrocarbons, causing environmental damage, economic losses, and public safety concerns [1].

The integrity of pipelines has been a subject of ongoing research and technological development. Traditional inspection tools, such as magnetic flux leakage (MFL) and ultrasonic devices, have been the mainstay of pipeline integrity management since the 1980s. These tools have proven effective in detecting corrosion, cracks, and other forms of damage. However, they face limitations when inspecting pipelines with complex geometries, such as tight bends, diameter changes, or non-circular valves [1,2]. These challenges are particularly acute for "unpiggable" pipelines — those that cannot accommodate conventional inspection tools. In the United States, approximately 70% of gas lines constructed before modern inline inspection (ILI) technologies were developed are considered unpiggable, representing up to 40% of pipelines in service as of 2012 [3,4].

Addressing the challenges of unpiggable pipelines requires innovative solutions. Advances in free-floating inline inspection tools since the early 2000s have opened new avenues for pipeline monitoring. These tools, which operate independently of pipeline geometry, are capable of detecting leaks [5,6], reconstructing pipeline paths [7,8], and assessing wall conditions [9,10]. Unlike traditional pigging devices that require continuous contact with the pipeline interior, free-floating tools navigate pipelines autonomously, collecting data as they move through the pipe. This capability allows them to operate in pipelines with complex geometries, including those with sharp bends, varying diameters, and non-standard features. Among their many applications, the use of remnant magnetometry for weld inspection is a promising area of research. This paper focuses on the application of principal component analysis (PCA) to remnant magnetization data, demonstrating its potential to identify welds with anomalous magnetic signatures and improve pipeline integrity management.

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Material Heterogeneity and the Challenges of Weld Inspection

Because welding is the only portion of the pipeline fabrication that occurs in the field, welds are less consistent than the rest of the steel pipe. As such, they are the most common locations for failures. Even a perfectly executed welding process introduces material heterogeneity, particularly in the heat-affected zone (HAZ) adjacent to the weld. This zone experiences significant thermal and mechanical changes, including grain coarsening, phase transformations, and residual stresses. The HAZ is particularly susceptible to stress-induced cracking and corrosion, making it a common failure point [11]. Additionally, weld defects such as porosity, incomplete fusion, and slag inclusions act as stress concentrators, further increasing the risk of failure [12]. Detecting these defects is a key objective of pipeline integrity management.

While traditional MFL devices have made significant strides in weld inspection, they face limitations in handling pipelines with complex geometries. Remnant magnetometry offers an alternative approach by analysing the residual magnetic signatures left by welding and other stress-inducing processes. These signatures provide valuable insights into the structural integrity of pipeline joints, enabling the identification of potential defects.

Principal Component Analysis: A Framework for Dimensional Reduction

The analysis of remnant magnetization data generates large datasets, particularly for long pipelines. For example, magnetometers on free-floating tools sample at frequencies of up to 1000 Hz, generating hundreds to thousands of data points per weld signature. Managing and interpreting such data requires effective dimensional reduction techniques.

Principal component analysis (PCA) is a statistical method that transforms high-dimensional data into a lower-dimensional space while preserving as much variance as possible. By performing a singular value decomposition on mean-centered data, PCA identifies a set of orthogonal eigenvectors, or "principal components," that capture the most significant patterns in the dataset.

In this study, these principal components are referred to as "eigenjoints," representing the magnetic signatures of pipeline joints. The explanatory power of each eigenjoint is quantified by its singular value, which provides a measure of the variance explained by that component. Cumulative energy plots visualize this information, illustrating how variance is distributed across the eigenjoints (**Figure 1**).

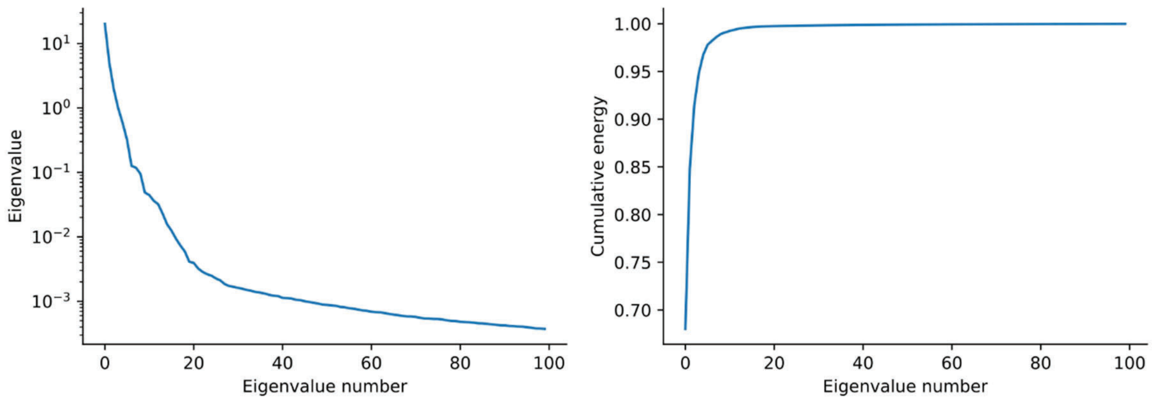

Figure 1. Cumulative energy plots of PCA analysis shows that less than 20 eigenjoints explain greater than 90% of the variance of the sample from this pipeline.

For the pipeline analyzed in this study, PCA revealed that the first eigenjoint captured 65% of the variance in the dataset, while the first 20 eigenjoints explained 98% of the variance. This finding highlights the effectiveness of PCA in reducing data complexity while retaining essential features.

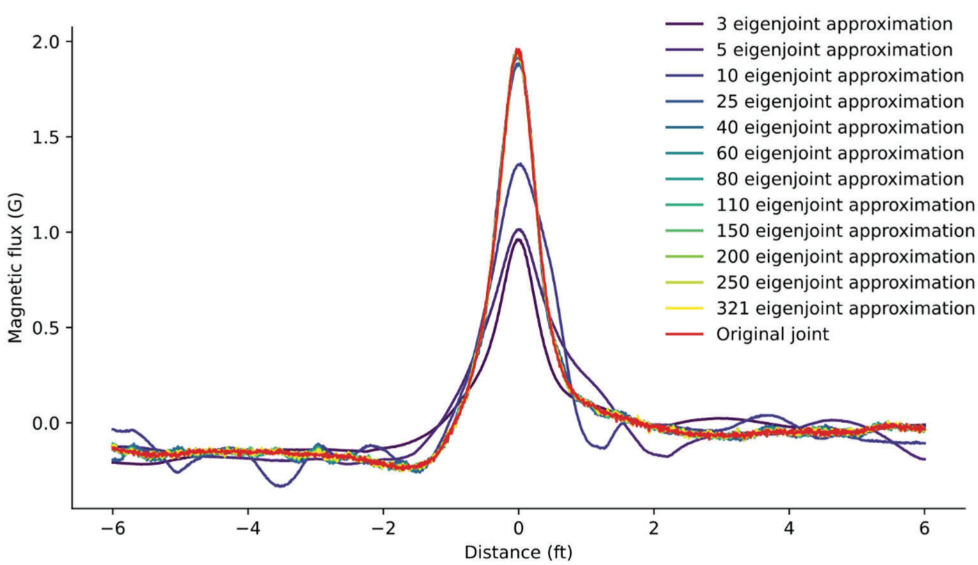

Figure 2. One of the typical joints in our sample is shown here as an approximation by a linear combination of increasing eigenjoints. At 25 eigenjoints, the approximation reproduces all features of the original signature.

By expressing each joint as a linear combination of eigenjoints, it becomes possible to classify welds based on the contributions to the various eigenjoints. Outlier joints, characterized by unusual magnetic signatures, can be identified by analysing deviations in eigenjoint contributions. An example of a magnetic signature reconstruction based on eigenjoint contributions is shown in **Figure**

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2. By using a linear combination of only 25 eigenjoints, we can reconstruct the magnetic flux density signature at every weld in the pipeline.

Results

The analysis focused on a pipeline segment containing 321 joints. Using PCA, the joints were categorized based on their eigenjoint contributions. Outliers were defined as joints where the contributions of the first two eigenjoints exceeded two standard deviations from the mean. The separation of joints by eigenjoint contributions is shown in **Figure 3**.

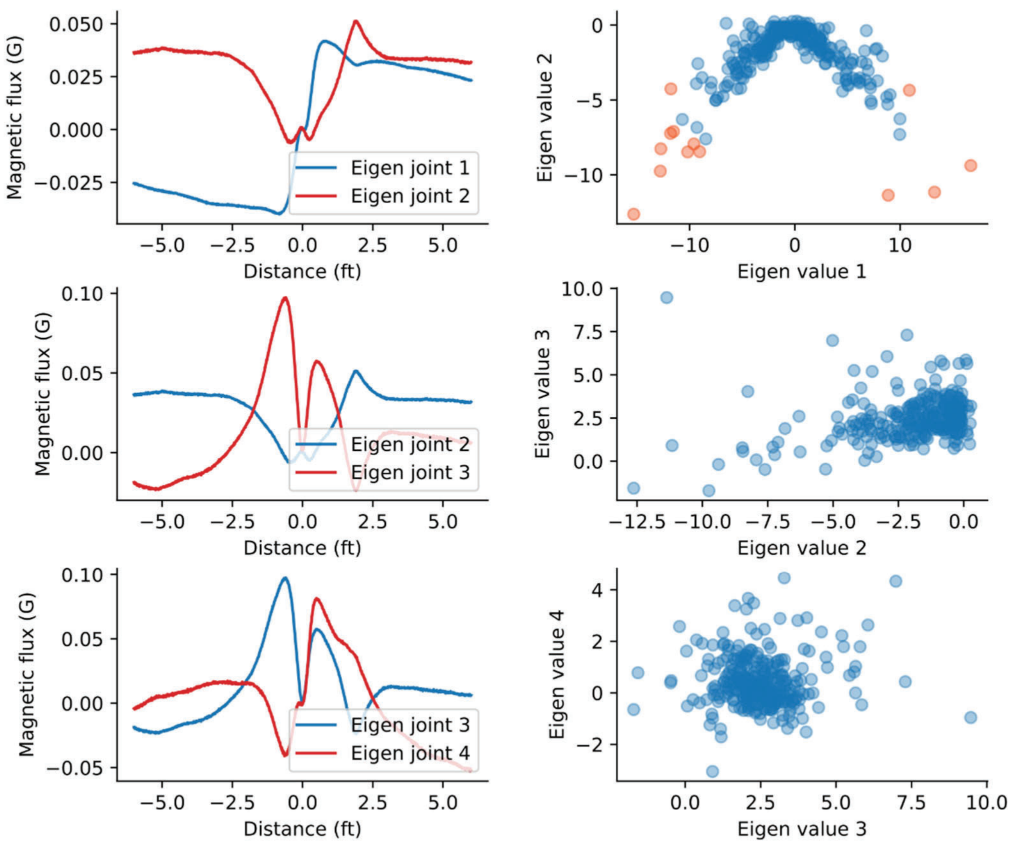

Figure 3. Comparison of the contributions of the first 4 eigenjoints to each of the real joint signatures in the sample. Outlier joints were defined as greater than two standard deviations in eigenjoints 1 and 2. In the upper right plot, those joints are colored orange to indicate outliers.

Outlier joints exhibited distinctive baseline offsets, a feature predominantly captured by the first eigenjoint. This baseline offset accounted for 65% of the variance in the dataset, demonstrating the power of PCA to identify key features without manual inspection. The offset is the most striking difference in the sample joints from the normal and outlier groups in **Figure 4**.

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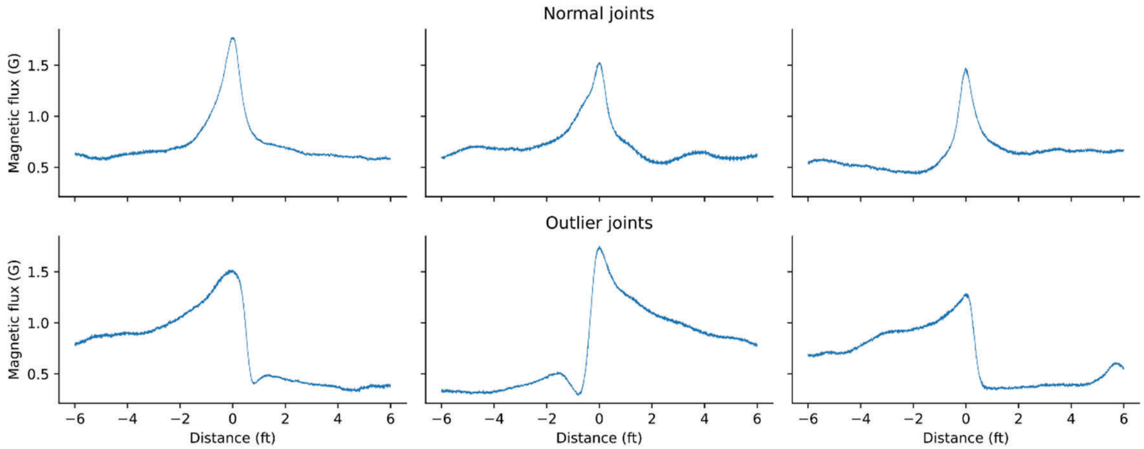

Figure 4. Samples of joints from the normal and outlier groups. The offset feature captured in eigenjoint 1 (see **Figure 3**) is the most pronounced difference between the two groups. This is expected as eigenjoint 1 is responsible for 65% of the variance within the joint signatures in this example pipeline.

Discussion

The application of PCA to remnant magnetometry data offers several advantages for pipeline integrity management:

Scalability: PCA is well-suited for analyzing large datasets, making it ideal for pipelines as long as free-floating devices can inspect.

Efficiency: By reducing the dimensionality of the data, PCA simplifies the classification of pipeline joints, allowing inspectors to focus on anomalies.

Insight: PCA quantifies the variance explained by specific features, providing a deeper understanding of pipeline joint morphology.

Future work will explore the integration of PCA with machine learning algorithms to automate anomaly detection. Techniques such as clustering and supervised classification have the potential to enhance the accuracy and reliability of joint classification. Additionally, expanding the dataset to include diverse pipeline materials and configurations will improve the generalizability of this approach.

Conclusion

This study demonstrates the potential of PCA in analysing remnant magnetic signatures of pipeline joints. By enabling efficient dimensional reduction and classification, PCA provides a powerful tool for managing unpiggable pipelines and detecting weld anomalies. As the field of remnant magnetometry continues to evolve, the integration of PCA with advanced analytics will further enhance pipeline integrity management.

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