Percussion-based Machine Learning Approach for Multi-Class Pipeline Inspection Gauge (PIG) Detection

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Problem Statement

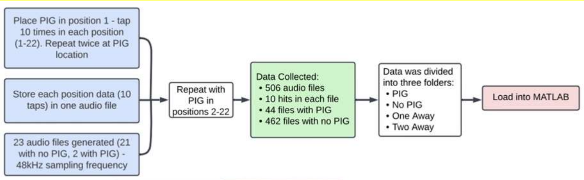
- The pipeline industry regularly uses PIGs (Pipeline Inspection Gauge) for inspection and cleaning of pipes. If PIGs get stuck in the pipeline during operation, they can be difficult to locate to clear out.
- This project introduces a percussion-based machine learning approach for PIG detection in a small pipeline. The project is extended to include multi-class detection to detect when the PIG is in close proximity to the tapping location.

Literature Review

- Current state-of-the-art methods to track PIG position and identify when it is stuck include but are not limited to on-the-field detection of vibrations, pressure/volume measurement, and dynamic flow simulation optimization loops.
- Limitations in these methods include low cost-effectiveness and reliance on passive measurements which results in loss of detection when the PIG gets stuck.

Experimental Setup and Collection of Data

- The data was collected by placing the PIG in each position on the pipe and tapping each spot 10 times for each PIG position.
- The position of the PIG was tapped 10 extra times in each position



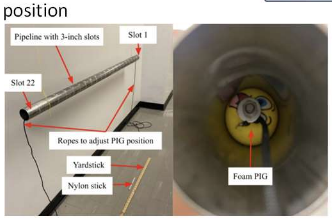


Figure 1: Experimental setup for data acquisition with labels on all major components

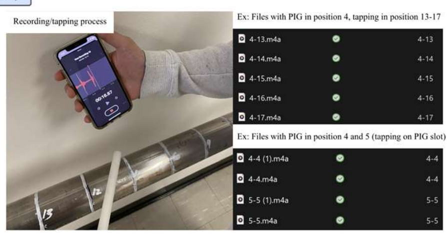
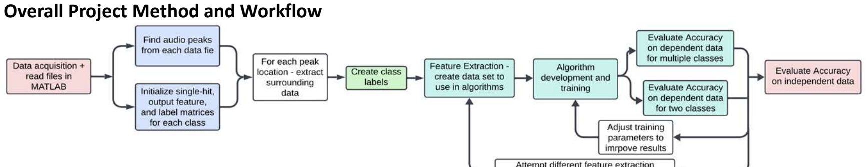


Figure 2: Recording/tapping process and naming conventions for audio files

Methods

Overall Project Method and Workflow



Final Signal Processing Method and Algorithms

Signal Processing Method

- Mel-frequency cepstral coefficients (MFCCs)

Shallow and Deep Learning Methods:

- Support Vector Machine (SVM)
- Neural Network (NN)
- Recurrent Neural Network (RNN)

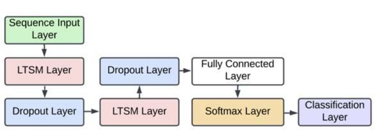


Figure 3: Flowchart of RNN layers

Comparison of Classes (time domain, MFCC features)

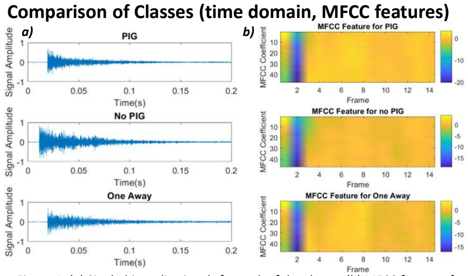


Figure 4: (a) Single-hit audio signals for each of the classes (b) MFCC features for each of the classes

Results, Analysis and Discussion

Dependent Validation Results

- Evaluated for two classes (PIG, no PIG), three classes (add One Away), and four classes (add Two Away)
- Split data so 70% was used for training, and 30% was used for validation
- To get a better understanding of the algorithms' capabilities to correctly identify the PIG, recall, precision, and F1 scores were calculated

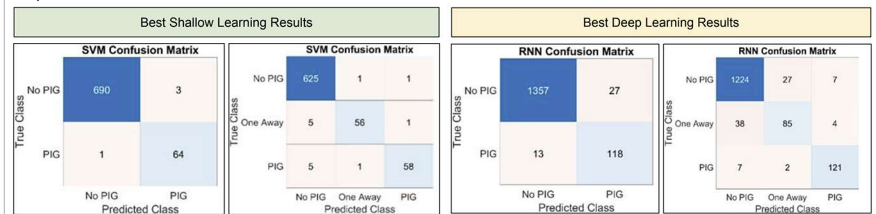


Figure 5: Confusion matrices for SVM and RNN validation for the two-class and three-class problem

Method (feature + algorithm)	Overall Accuracy (2 classes)	Overall Accuracy (3 classes)	Overall Accuracy (4 classes)
MFCC + SVM	99.40%	98.07%	96.21%
MFCC + NN	98.47%	95.02%	90.82%
MFCC + RNN	97.36%	94.39%	N/A

Table 1: Accuracy for dependent validation for SVM, NN, and RNN

Method (feature + algorithm)	Recall		Precision		F1-score	
	2 classes	3 classes	2 classes	3 classes	2 classes	3 classes
MFCC + SVM	98.46%	90.63%	95.22%	96.67%	96.97%	93.55%
MFCC + NN	93.85%	90.63%	95.31%	93.55%	94.57%	92.07%
MFCC + RNN	90.07%	93.08%	81.37%	91.67%	85.78%	92.40%

Table 2: Recall, precision, and F1 score for PIG detection (positive)

Independent Validation Results

- Independent data validation was performed for two- and three-class problems for NN and SVM – recall, precision, and F1-score were computed for the two-class case

Method (feature + algorithm)	Overall Accuracy (2 classes)	Overall Accuracy (3 classes)	Recall (2 classes)	Precision (2 classes)	F1-score (2 classes)
MFCC + SVM	94.18%	82.93%	57.27%	92.64%	70.87%
MFCC + NN	95.21%	83.33%	55.45%	85.91%	67.40%

Table 3: Accuracy, recall, precision, and F1-score for the independent data validation

Analysis and Discussion

- Successful PIG detection was achieved on dependent testing data for all algorithms used. Positions up to two away could be successfully detected with only a slight decrease in overall accuracy.
- The SVM model performed the best in all evaluated classification tasks. It achieved high recall and precision values, indicating that the PIG detection was successful for both two and three classes.
- The independent validation results showed overall good accuracy (>95%) but had a decrease in recall and precision, indicating that the algorithms can be made more robust.

Conclusion

- The percussion-based data collection using MFCC features in combination with SVM, NN, and RNN algorithms performed well for up to **four-class position classification and PIG detection**.
- The SVM algorithm performed the best and obtained over 95% accuracy and 93% F1-score for the investigated classification problems.
- **Future work**: Apply methods to reduce the risk of overfitting (ex. Regularization), and further investigate more complex deep learning models.
- Extract more relevant features, transform existing features, or create new ones that better capture data trends.
- More data collection and using cross-validation on independent data during the algorithm training

Acknowledgements

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References

[1] G. Bernasconi and G. Giunta, "Acoustic detection and tracking of a pipeline inspection gauge," *Journal of Petroleum Science and Engineering*, 2020, Vol 194.
[2] G. Hiltscher, W. Mühlthaler, J. Smits, *Industrial Pigging Technology: Fundamentals, Components, Applications*, John Wiley & Sons, 2006, ISBN: 9783527609055,
[3] L. Guan, Y. Gao, H. Liu, W. An and A. Noureldin, "A Review on Small-Diameter Pipeline Inspection Gauge Localization Techniques: Problems, Methods and Challenges," *2019 International Conference on Communications, Signal Processing, and their Applications (ICCSPA)*, 2019, pp. 1-6.
[4] G. Giunta et al., "Method And System For The Continuous Remote Tracking Of A PIG Device And Detection Of Anomalies Inside A Pressurized Pipeline". United States Patent US 10,132,823 B2, Nov. 20, 2018.
[5] M. S. Chowdhury, and M. F. Abdel-Hafez, "Pipeline Inspection Gauge Position Estimation Using Inertial Measurement Unit, Odometer, and a Set of Reference Stations." *ASME. ASME J. Risk Uncertainty Part B.* 2016, 2(2): 021001.