Project Title: Pipe Pig Detection using Percussion Tapping with Machine Learning

Rami El-Haibe, Undergrad Student

Department of Mechanical Engineering, Cullen College of Engineering

Problem Statement

Pipe pigging refers to the use of a cylindrical foamlike object (pig) to clean and inspect pipelines by passing through the pipeline. In long pipelines, issues arise in locating the pig, and oftentimes pigs can be completely lost. This experiment aims to employ percussion tapping with machine learning to identify the exact location of the pig. Successfully classifying the pig location will have a broad impact in the nondestructive testing industry, allowing technicians to easily and cheaply locate lost pigs.

Brief Literature Review

Current research does not involve machine learning extensively. Acoustic detection of pig location has been investigated via amplification of the pig movement through the pipe [1]. Additionally, remote sensing via acoustic senor arrays have proven useful [2]. These systems use centralized controllers to identify hydraulic and acoustic transients to ultimately detect the pig location.

Experimental Setup and Collection of Data

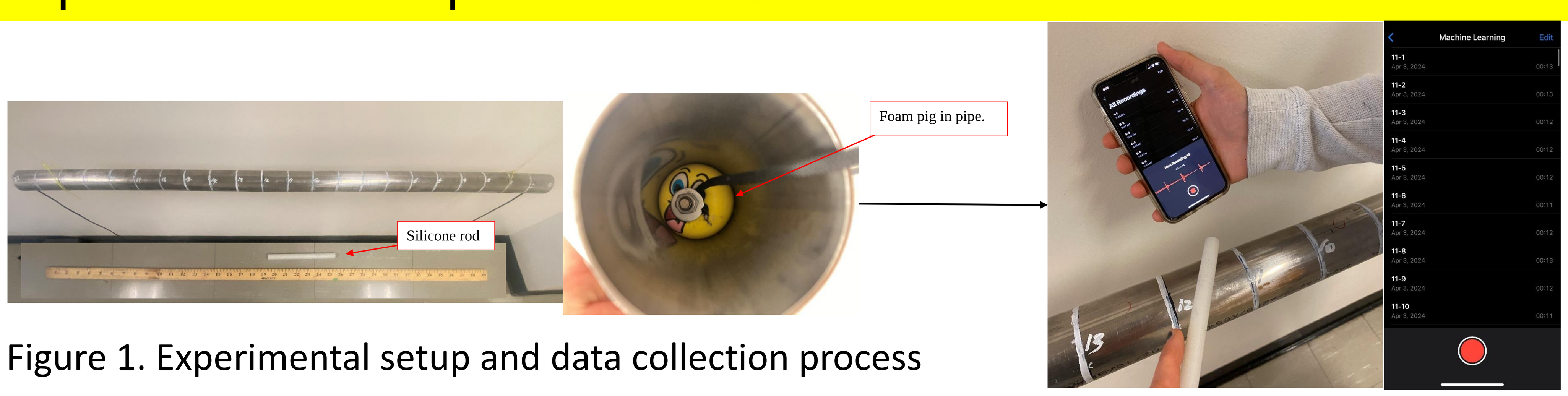


Figure 1. Experimental setup and data collection process

- Voice Memos app with a 48kHz sampling rate was used with one student recording and the other tapping. Pig was inserted into first segment and 10 hits were collected at each segment, 20 for the pig segment. Pig would then be moved up to segment 2 and the process was repeated through the entire 22 segments
- 22 audio files recorded for each pig placement for a total of 484 files, and 5060 individual hits, however, the first hit from each file was excluded from the dataset, resulting in 4549 total hits in the dataset.
- Naming convention followed an X-Y format, where X is the pig location, Y is the segment # being tapped. (Example shown for 1-2: pig in segment 1, taps Conducted on segment 2).

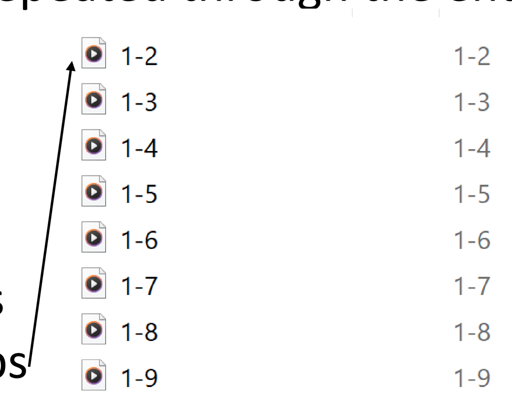


Fig 2. Audio files for pig located in segment 1

Method(s)

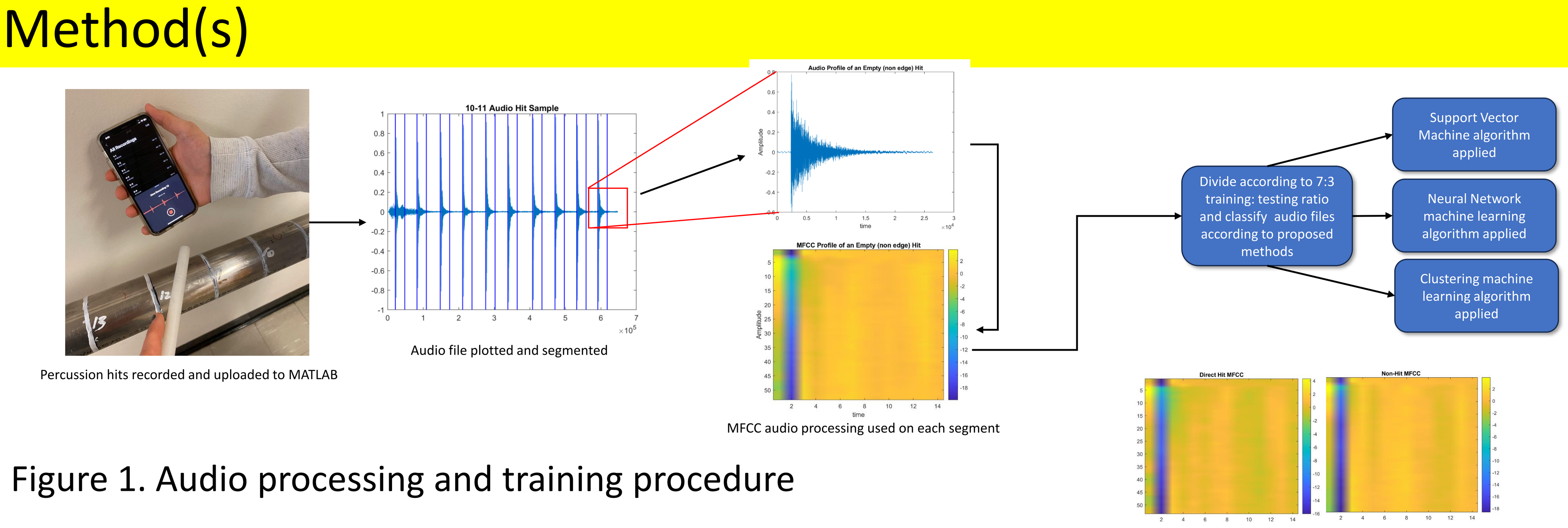
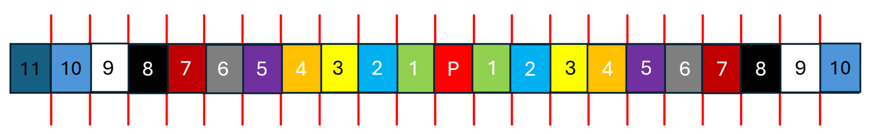


Figure 1. Audio processing and training procedure

Fig 2. Pig segment MFCC processing (left) versus empty hit (right)

- All audio processed via MFCC signal processing.
- Method 1 uses 2 class classification for "Exact hit" and "Empty hit" segments labeled as 2 and 3 respectively in code. Two main machine learning algorithms, NN and SVM used to train data.
- Method 2 uses 3 class classification for "Exact hit (2)," "Empty hit (3) ," and "Edge (1)" and aims to gauge algorithm's ability to differentiate between an empty segment and one that is specifically an edge piece.

INNOVATION



- The project scope was expanded to a 13-class classification of the pipe, attempting to classify the pig location and its 11 neighboring empty segments, theoretically classifying every pipe segment. This expands on "method 3" which measures the first neighboring segment.

Results, Analysis and Discussion

Method	KNN Accuracy	SVM Accuracy	NN Accuracy	RNN Accuracy
1	97.65%	98.4%	98.9%	~
2	99.4%	91.5%	98.24%	92.6%
3	95.82%	93.6%	98%	95%
4	84.61%	64%	77.21%	10%

Table 1. All method algorithm accuracies

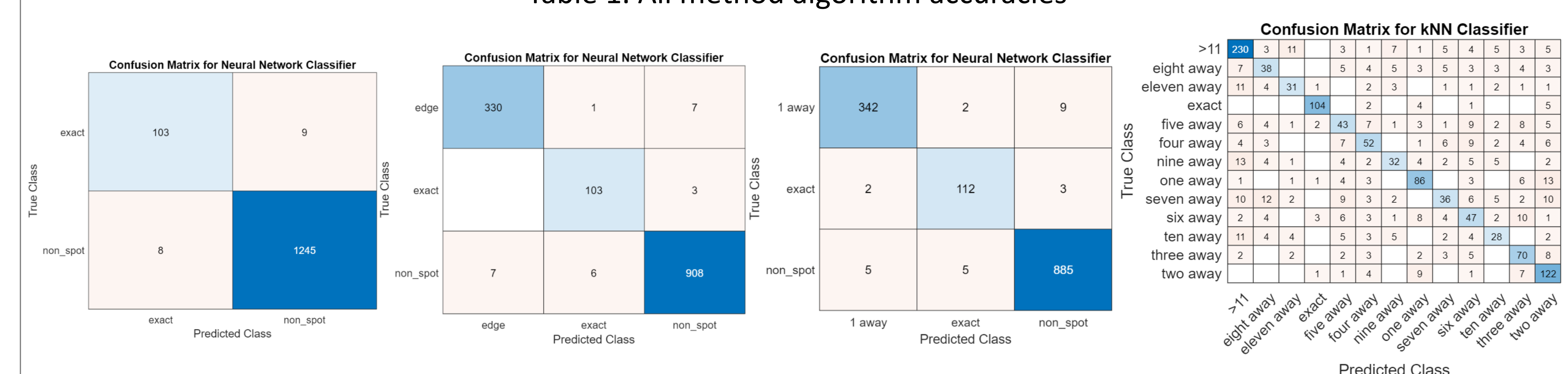


Figure. 4 (left to right) Confusion matrices for NN with method 1,2,3 and new method (4)

- NN/ KNN provided highest accuracy in all methods. Determining pig location in simple hit vs no hit resulted in >98% accuracy.
- Edges were detected with high accuracy; model was able to differentiate between a regular empty segment and an empty edge segment

method	Recall	Precision	F1 Score
1	0.956	0.960	0.958
2	0.977	0.968	0.972
3	0.971	0.969	0.970

Table 2. Methods 1-3 Performance indexes

- New method (4) showed promising results (77% with NN) and could reliably classify the two nearest neighbors. With shallow learning methods, models misclassify neighboring segments rather than providing a compete misclassification.
- Despite the dataset containing the six edge pieces, reducing the quality of the dataset, the model was still able to correctly classify all empty segments properly in method 1, while making the proper distinction in method 2.

Conclusion

- Models achieved very high accuracy in methods 1-3 with two to three classes, confirming the feasibility of percussion tapping for pig detection
- The novel method had satisfactory accuracy with 77% with NN; with further improvements with normalization and optimizing the model, such a method could prove to be very beneficial for an operator.
- The fundamental theory has been confirmed by this research, the next steps would be to improve accuracy for multi class classification using reliable independent data and assess other signal decomposition methods.

Acknowledgements

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References (brief)

[1] Brown, Robert C., and John D. McIntyre. PIPELINE PIG TRACKING . 27 May 1986.

[2] Giunta, Giuseppe, et al. Method and System for the Continuous Remote Tracking of a Pig Device and Detection of Anomalies inside a Pressurized Pipeline. 20 Nov. 2018.