Non-Invasive Water Level Detection Using ML

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Problem Statement

- The goal of this project is to develop a reliable machine learning model for detecting the water level inside of a metal container using the sounds made by tapping on the container. The amount of water inside of the container will influence the sound waves produced by the tapping (non-invasive liquid level detection). Using MFCC feature extraction, the aim is to train multiple machine learning models to accurately predict the water level inside of the container.

Brief Literature Review

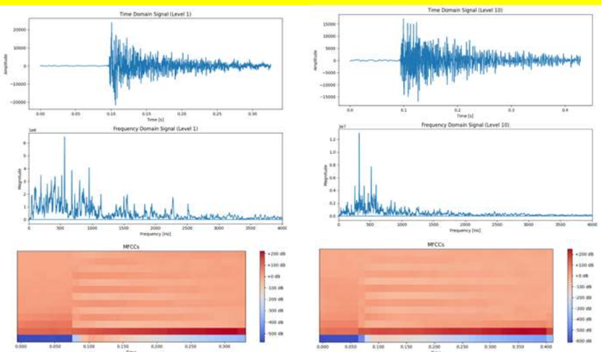
- Liquid Level Measurement Model Outside of Closed Containers Based on Continuous Sound Wave Amplitude by Yanjun Zhang, Bin Zhang, Liang Zhang, Yunchao Li, Xiaolong Gao, and Zhaojun Liu
- SoQr: sonically quantifying the content level inside containers by Mingming Fan and Khai N. Truong

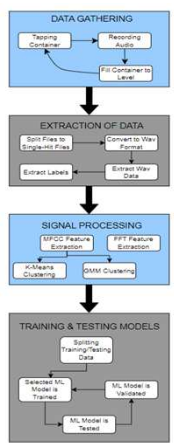
Experimental Setup and Collection of Data

Level of Fill	Percent Fill	Volume (ft^3)	Total Hits
1 (empty)	10%	0.22	340
2	20%	0.44	341
3	30%	0.66	342
4	40%	0.88	338
5	50%	1.10	342
6	60%	1.32	340
7	70%	1.55	343
8	80%	1.77	340
9	90%	1.99	339
10 (full)	100%	2.21	339

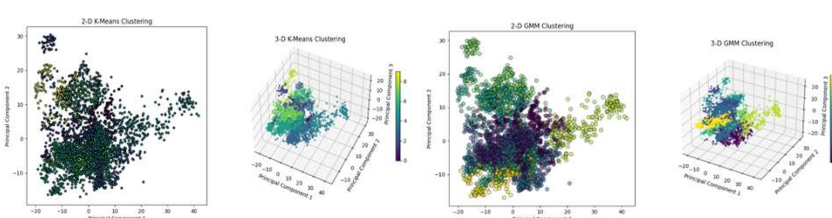
- Data was collected during 6 different days using a Samsung Galaxy S10, everyday steel hammer, 60-liter aluminum stockpot on top of a wooden stool.
- Data was gathered in an open-air back porch with moderate background noise.
- A total of 3604 single hit data points.

Methods





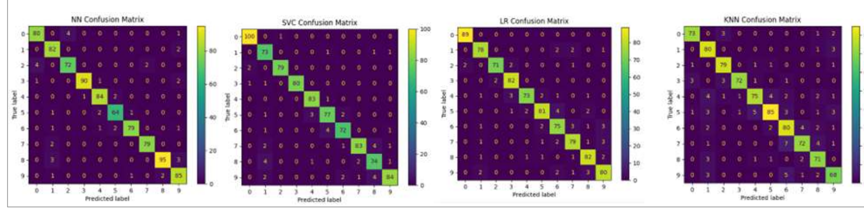
- Using signal processing toolkits in python, the Mel-Frequency Cepstral Coefficients (MFCCs) and Fast Fourier Transform (FFT) features were extracted for each audio recording.
- K-Means and GMM clustering methods were performed.



Results, Analysis and Discussion

The performance of multiple machine learning models in predicting the water level inside of the container based on MFCC features was evaluated. These classification models showed various degrees of accuracy as shown below:

- The Neural Network (NN) model achieved the highest accuracy of 96%. Using a total of 2 hidden layers with 500 neurons each, the model performed best. The validation data accuracy was also the best for this model with approximately 80%. This NN model proved to be least accurate for label 5. This is an interesting observation because the fill level lines up directly with the impact zone on the outside of the stock pot for level 5.
- The Support Vector Machine (SVC) model had a high accuracy of 95%. SVC can handle both linear and non-linear decision boundaries. The validation data accuracy for this model was also close to 80% accurate. This model's confusion matrix shows that it was most accurate for the lower labels (lower fill).
- The Logistical Regression (LR) model also had a relatively high accuracy of 93%. The 'one vs all' multi-class classification proved to perform well with the MFCC features extracted from the audio signals. The LR model's confusion matrix shows that most of the missed predictions are right above or right below the true label. Something that is also true for KNN, but not as much for LR and NN.
- The K Nearest Neighbor (KNN) model performed with an accuracy of 89%. A K value of 2 or 3 seemed to be what worked best for this model. The model appeared to be easily overfitted, and therefore a low value of K was selected.



Conclusion

- The SVM and NN models performed the best and offered the highest accuracy, as expected. The robustness of these models proved to be critical when handling the complex MFCC features. On the contrary, the LR and KNN models were less robust and are better at classification for more local data points.
- The clustering methods performed showed some differences between the two models (K-Means vs GMM). The algorithm for each of the models is seen in the diagrams provided. The principal features extracted provided only a limited view into the features since not all of the features are modeled in that diagram.
- For better results, the data gathering could be performed in less noisy environment for more accurate results and training of the model. Additionally, the more points that were gathered, the higher the accuracy for all the models. Therefore, a higher pool of data could help improve the results, even with a noisy environment. In fact, this may help with the robustness and realistic data gathering process for many industrial and non-industrial applications.

Acknowledgements

- The financial support from Midstream Integrity Services (MIS) and technical support from Smart Materials & Structures Lab (SMSL) and Artificial Intelligence Lab for Monitoring & Inspection (AILMI) at UH.
- Dr. Gangbing Song
- Cory Crow
- Jian Chen

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