Environmental Noise Contamination Detection

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Project Overview

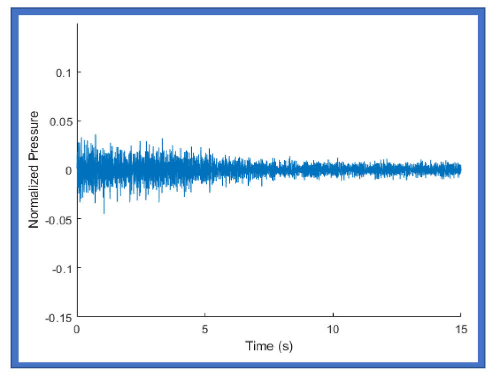
Background
- Public demand for reduced noise population forcing regulatory agencies to reduce aircraft noise limits
- Certification process is expensive
- Monitoring personnel used to lower risk of higher certified noise levels by noise contamination
- Contamination sources include birds, insects, livestock, and road traffic

Objective
Research the feasibility of automating the detection of environmental noise contained in acoustic measurements for aircraft community noise testing.

Data

Audio Files
- 72 Total
- Clean Signals
  - 59 Aircraft and Ambient Recordings
- Contamination Signals
  - 13 Animal Vocalizations

Process
- Aircraft audio file split into blocks to generate features
- Contamination audio file chosen and split into blocks
- Contamination added to aircraft signal with desired signal-to-noise ratio
- Repeated for all aircraft audio files
- All generated features combined into set for model training



Methods

Our investigation into the viability of automated detection of environmental noise contamination is broken into two parts. A broad assessment of feature sets and models followed by a deeper investigation into three of the best performing pairs.

Broad Investigation
Objective: To gain insight to which broad categories of feature sets and model combinations might provide the best prediction accuracy
- Signal-to-noise ratio held at 6 dB
- Block size limited to only 1 seconds or 2 seconds
- Used default hyperparameters and settings when training models

Deep Investigation
Objective: To optimize a limited set of feature set and model combinations for their best performance and subject them to rigorous testing to understand real-world performance
1. Optimize the models hyperparameters.
2. Randomize the signal-to-noise ratio.
3. Randomize the percent of a block that contains contaminated audio.
4. Randomize which blocks are contaminated.
5. Vary all of above parameters through Monte-Carlo simulation.

Broad Investigation Results

The three feature set, classifier pairs selected for detailed study are as follows:

- **Model**: Bagged Trees
- **Feature:** Wavelets (Coiflet2, 5 level, T=2s)
- Best overall with accuracy of 94.2%

- **Model**: Bagged Trees
- **Feature:** Wavelets (Coiflet2, 4 level, T=2s)
- Accuracy of 93.3%

- **Model**: Cubic SVM
- **Feature:** Cepstral (26 feature T=2s)
- Best non-NN, non-wavelet performer with accuracy of 92.8%

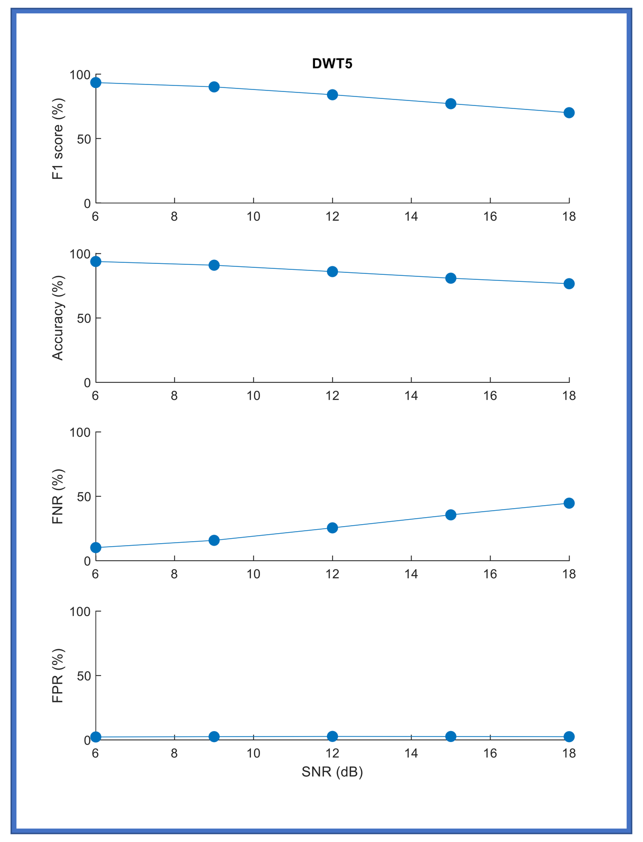
Deep Investigation Results

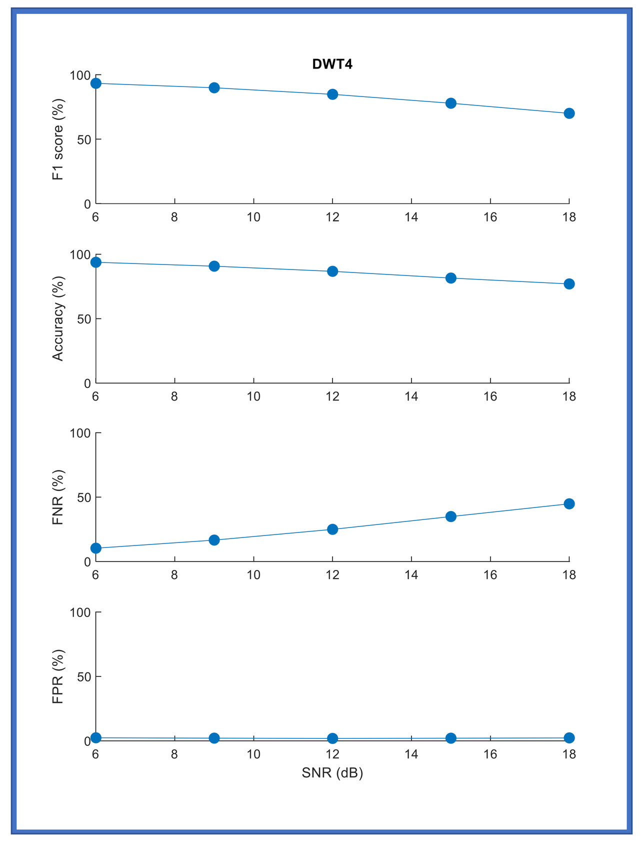
Performance summary of optimized feature set and classifier pairs for detailed study subjected to randomized signal blocks contaminated

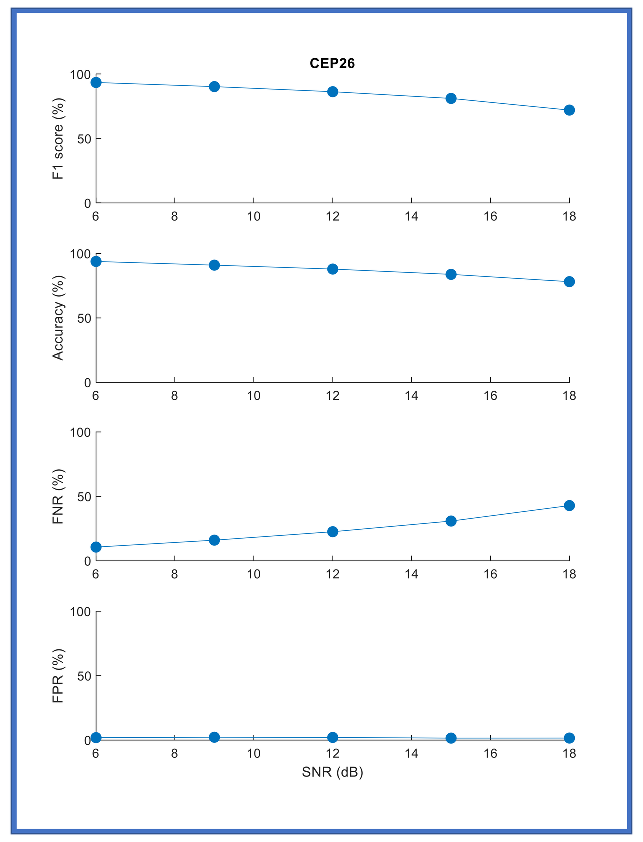
	F1 SCORE	ACCURACY	FNR	FPR
DWT5	93.4%	93.6%	10.4%	2.4%
DWT4	93.6%	93.8%	10.1%	2.2%
CEP26	93.6%	93.9%	10.3%	1.9%

Signal-To-Noise Ratio – Parameter Sweeps

For each of the optimized feature set and classifier pairs, we observed that as the signal-to-noise ratio increased, this resulted in less accuracy due to the models inability to detect contaminated blocks.







Glossary

Mel-Frequency Cepstral Coefficients (MFCC)
Coefficients that are derived from a non-linear transform of a spectrum that are equally spaced on the mel scale.

Wavelet
Definition of wavelet goes here

Coiflet2
Definition of Coiflet2 goes here

Signal-To-Noise Ratio
A ratio comparing the level of a clean signal to the level of the background noise.

Something Else?

Challenges

How To Turn Audio Into Features
We separated each audio file up into blocks of an equivalent length and then processed the features for each block. Blocks from which features were generated could contain overlapping audio.

How To Quantify Contamination Levels
The audio recordings that were used only had a single source of noise allowing us to combine aircraft or ambient signals with contamination to create a larger data set than the 66 files. This also allowed us to control the signal-to-noise ratio.

Limitations

Due to the small size of potential contamination audio, the models are not as accurate when classifying new sources of contamination.

One recommendation that we do have at this time is that we suggest that more data is provided to fully enumerate the possible contamination classes that would exist near the test site.

Results

- Wide variety of feature sets and classifiers show potential to achieve an accuracy >90%
- Deep neural networks under performed as compared to more traditional classifiers
- Computation time of the feature set required for the combination influenced the selection of 3 combinations to optimize
- 3 optimized feature sets and classifiers achieve >93% cross-validation accuracy
- Performance of all 3 degraded when tested against randomized scenarios
- Increased fidelity of DWT5 did not out perform DWT4

Recommendations

- Continue with the DWT4 and CEP26 feature sets and classifiers
- Expand the data sets with additional data, more constructed scenarios, and with variation in the signal-to-noise ratio
- Development method to compute the effective signal-to-noise ratio for the scenario with a reduction in the proportion of the signal block contaminated

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