Outline of Introduction

All commercial aircraft must be certified by government agency for noise levels

This requires testing final design and build aircraft by flying the aircraft over acoustic instrumentation as required by the regulations (See FARS 36 and ICAO Annex 16)

This is expensive (try to find public reference for hourly cost of test flight time or noise certification testing) and thus don’t want to repeat, thus want quietist acoustic signature recordings possible

Any contamination of the acoustic signal from the aircraft risks increase certified aircraft noise levels, non-compliance with customer guarantees, and at worst a failed certification test

Currently solutions include using test locations with low background noise levels (https://www.washingtonpost.com/news/wonk/wp/2018/02/20/using-the-best-data-possible-we-set-out-to-find-the-middle-of-nowhere/?utm\_term=.c8622cb9579a), human monitoring of acoustic recordings for biological vocalizations (birds, insects, livestock) or machinery noise (road traffic noise, other aircraft, farm equipment)

Problem is people are expansive and require expensive equipment

Propose feasibility study into using machine learning algorithms to automatically detect contamination

[7]

In Adavanne et al, LSTM units (Long short-term memory) within a Recurrent Neural Network (RNN) are leveraged to identify sound events in polyphonic audio samples [7]. Three different feature sets were studied: log mel-band energy, harmonic features (such as pitch), and time difference of arrival (TDOA). A combination of mel-band energy and TDOA features performed the best in this context.

[8] and [9]

Royo-Letelier et al [8] explored the use of metric learning to disambiguate artists within a music catalog. They found that at smaller dataset sizes (300 or fewer examples), that a traditional 1D-CNN (One Dimensional Convolutional Neural Network) outperformed the metric learning model [8]. The model they compared their metric learning model to is described in [9].

In [8], triplet loss was used to separate different groups of musicians. This loss mechanism learns a metric preserving map *f* that groups similar pairs and distances dissimilar pairs given a triplet of (xa, x+, x-).

Volker B. Deecke and Vincent M. Janik. “Automated categorization of bioacoustics signals: Avoiding perceptual pitfalls.” Journal of the Acoustical Society of America, vol. 119, no. 1, pp. 645-653, 2006.

The authors present data and results of using unsupervised learning to categorize animal vocalizations into meaningful biologically relevant categories. Used ‘known’ data from bottlenose dolphins and orca whales. The data was categorized by and agreed upon by humans specialists. Algorithm only referenced and not provided in paper. Used dynamic time warping and adaptive resonance theory neural networks of ‘frequency contours’ of the biological acoustic signals. These ideas leverage the natural features of sound by vertebrate auditory perception:

1. Relatively insensitive to changes in the duration of a vocalization pattern. Animals don’t care if the vocalization duration is different by small amounts, more sensitive to frequency changes.
2. Frequency perception is nonlinear. Frequency perception is on logarithmic scale, octaves.

Need to allow for adjusting the duration of a signal feature when comparing to a known example, and work with octave frequencies. The adaptive resonance theory 2 neural network compares a signal to a set of references, if close categorize with reference, else make new reference category. Demonstrated improved accuracy of categorization as compared to human observers and improved consistency. The automated method was returned the same categorization for a given data set.

* Supports the use of octave filters

# References

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