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

Can an algorithm detect that an aircraft signature is contaminated with biological noise?

Outline remainder of paper

Background (including previous work)

training

Acquire signals with known provenance

Prediction (offline or streaming)

Acquire signal

Segment signal as done for training data

Run each segment through trained classifier to make predicted class (clean vs contaminated)

Raise alert and log data if contaminated

[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

**Wavelets**

*Still very much scratch work.*

It is well-known that Fourier and other spectral analyses are cornerstone to signal processing. The Fourier Transform, for example, decomposes a signal into a set of sine and cosine basis functions of different frequencies, thereby transforming a given signal into a corresponding frequency domain representation. Feature extraction can thusly be deployed by analyzing key characteristics – such as ‘spectral’ energy in various passbands or FFT coefficients at important frequencies.

However, signal classification techniques using feature extraction via the Fourier Transform pose one limitation: the time-axis is ignored. Namely, using solely Fourier techniques on the entire signal prevent a full comprehensive analysis of signals such as audio, where time is a crucial factor – we seek to examine “where” and “when” important spectral coefficients emerge. This notion is the uncertainity principle in signal processing: the cost of higher resolution in time domain is lower resolution in the frequency domain, and vice versa

A solution to the joint time-frequency analysis problem has been the Short-Term Fourier Transform (STFT), which injects a sliding window function into the main equation of the Discrete Fourier Transform. However, the STFT resultantly creates uniformity in the time vs. frequency “plane.” This can be disadvantageous in certain applications, especially audio signal processing and human acoustics, where frequencies of interest lie on an octave/dyadic “logarithmic” scale.

A more modern approach to the joint time-frequency problem has been the Wavelet Transform.

The Discrete Wavelet Transform (DWT) and Discrete Wavelet Packet Transform (DWPT) have been

The following features are used in our system:

* The mean of the absolute value of the coefficients in each subband. These features provide information about the frequency  distribution of the audio signal.
* The standard deviation of the coefficients in

each subband. These features provide information about the amount of change of the frequency distribution

ï Ratios of the mean values between adjacent subbands. These features also provide information about the frequency distribution. (averaging approach across the possible resolutions)

approximation and lowest detail level, so I suspected that this was overkill. To test this hypothesis, I ran classification experiments using the Daubechies wavelet family at various decomposition levels for feature extraction. The resulting success rate at each of 8 different levels, averaged across db1 through db8 wavelets, is shown in Figure 5. Unlike the MFCCs, where the success rate was not a smooth function of the number of coefficients, with the wavelet decomposition there is a reasonably smooth increase in success rate as the number decomposition levels increases, up until the highest number of levels, where as expected, the small size of the resulting final band was likely more misleading than helpful. While the highest average success rate occurred at 11 levels, the highest rate for an individual wavelet was the db6 wavelet at 8 levels (71.33%). The db4 wavelet at 8 levels was almost as effective as db6, with 68.67% success. The highest success rate at 11 levels was 69.33%, so even though the average success rate was higher elsewhere, I chose the db4 wavelet with an 8-level decomposition as the ideal balance of computational complexity (filter length and decomposition levels) and success rate. Later comparisons with MFCCs were all performed using this wavelet.

(Michelle)

Matlab – specific decomposition level – spectral energies and

**References to Add:**

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From before

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