
# Identification of Songbird Species in Field Recordings

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## Introduction

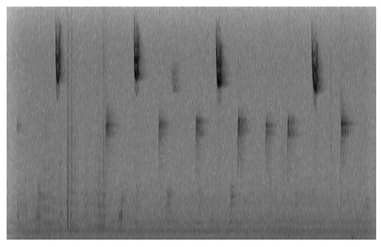
It is important to gain a better understanding about the climate and ecological changes in the world. One way to address this is to study seasonal migration patterns in songbird populations, since birds respond quickly to environmental changes During migratory periods, many species of songbirds use flight calls, which are species-specific and are distinct from other vocalizations. Therefore, flight calls information can be used to determine the relative abundance of species and is important to understand long-term population trends. Due to costly human effort to collect data about birds in traditional methods, using machine learing (ML) methods to identify bird species from continuous audio recordings has been a hot topic in in recent conference competitions. Although there are some recent advances it is still an open ML problem to reliably identify bird sounds in field recordings data due to simultaneously vocalizing birds and various background noise.

## Features

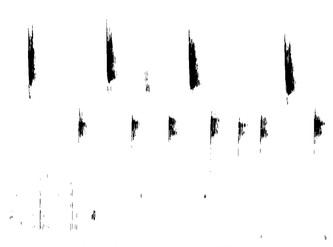
- Spectrogram based (cite Briggs):
  - Mask descriptors:
    - min-$f$, max-$f$, bandwidth (min-max), duration (T)
    - area, perimeter, non-compactness, rectangularity
  - Profile statistics:
    - gini, mean, variance, skewness, kurtosis,
    - area, perimeter, non-compactness, rectangularity
  - Histogram of gradients (HOG)
- Mel-Frequency Cepstrum Coefficients (MFCC) based:
  - Has been successful in speech recognition.
  - 39 dimensional vector. First dimension is energy.
  - $T \times 39$ matrix $M$ for each audio file ($T$ is not fixed.)
  - Continuous features: $\frac{1}{T}\sum_t M_t$, $M_{t_{max}}$, and first PC of $M$
  - Discretized features: Quantize MFCC by k-means. ($K = 200$)
    - Bag-of-words: 200-D histogram
    - N-gram ($N = 2, 3$): $200^N$-D histogram. Select occurrence $\geq 3$.
  - Denoising: Only use $t$ with energy above threshold.

## Preprocessing/Segmentation

We first convert audio files into spectrogram images, and for each segments we use Hanning windows with %75 overlap. Notice the case that in a processed grayscale image most area was occupied by the random noise. What we want is to get rid of the background noise completely and increase the contrast between real signal and the background. Given the several different algorithm tested, the median clipping algorithm works best because it not only removes most background noise, but also capture the sound feature clearly and precisely.

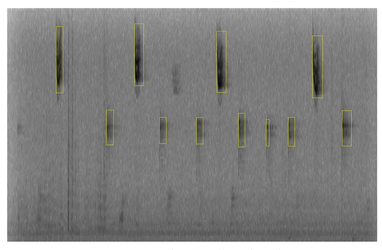


a. Original Spectrogram



b. Median Clipped

c.Eroded and Propagated



d. Labeled

## Classifiers/Ensembles

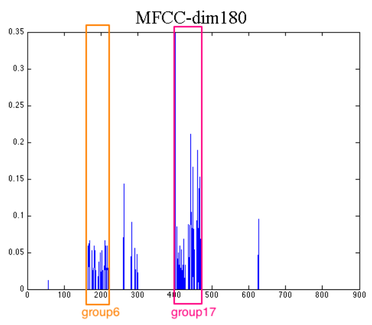
The classifiers we used are

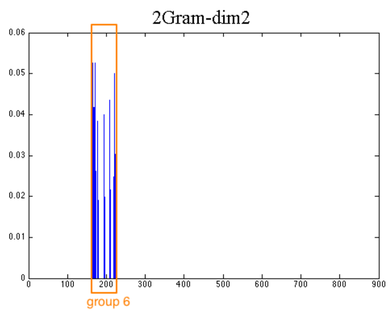
**Nearest Neighbor (NN).** We used euclidean and $\chi^2$ distance.

**Support Vector Machine (SVM).** This is the most common approach for multi-label classification. We tried linear SVM, sigmoid SVM and SVM with polynomial and rbf kernel.

**Random Forest.** Random Forest is operated by constructing decision tree structure by the training examples.

## Experiment




The accuarcy for classifier (using Random Forest) on features extracted by the baseline method is 0.25.

| Classifier | Accuracy | Features | Settings |
|---|---|---|---|
| linear SVM | 67.7273 | BoW | |
| | 70.4545 | denoised BoW | |
| poly SVM | 69.0909 | BoW | |
| | 70.4545 | denoised BoW | degree: 1 |
| | 70 | denoised BoW | degree: 2 |
| | 70.4545 | denoised BoW | degree: 3 |
| rbf SVM | 70 | BoW | |
| | 68 | BoW (log) | |
| | 70.4545 | denoised BoW | |
| | 76.8182 | denoised BoW | $\gamma = 7.9433$ |
| | **78.1818** | denoised BoW + 2gram | |
| sigmoid SVM | 70.9091 | BoW | |
| | 70.4545 | denoised BoW | |
| random forest | 57 | denoised BoW | 100 trees; 5 splits |
| | 63 | denoised BoW | 100 trees; 2 splits |
| NN-euclidean | 54.09 | BoW | |
| | 62.73 | denoised BoW | |
| NN-chisquare | 62.27 | BoW | |
| | 71.82 | denoised BoW | |