Assistive Classification for Improving the Efficiency of Avian Species Richness Surveys

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***Abstract*— Avian species richness surveys, which measure the total number of unique avian species, can be conducted via remote acoustic sensors. An immense quantity of data can be collected, which, although rich in useful information, places a great workload on the scientists who manually inspect the audio. To deal with this big data problem, we calculated acoustic indices from audio data at a one-minute resolution and used them to classify one-minute recordings into five classes. By filtering out the non-avian minutes, we can reduce the amount of data by about 50% and improve the efficiency of determining avian species richness. The experimental results show that, given 60 one-minute samples, our approach enables to direct ecologists to find about 10% more avian species.**

***Keywords*— classification; avian species richness; acoustic sensor data; acoustic indices**

I. Introduction

Avian species richness studies the number of unique avian species in a particular area given a fixed period of time. The study of aves (a Latin word refers to birds) has several ecological reasons. First, in terms of monitoring the natural environment, avian species are a good indicator of dynamic environmental changes [1]. Second, acoustic monitoring has the potential to be conducted at large spatial and temporal scales, because avian species spread over a wide range of landscape and vocalize more often than other species do. Third, the knowledge on their behavior is well established [2].

Acoustics have long been used to monitor the natural environment and its inhabitants [3, 4]. Thanks to advances in acoustic sensors, acoustic data now can be collected at a large spatiotemporal scale [5]. The advantages of deploying acoustic sensors are that they enable to record continuously and the data can be stored permanently once collected. However, this presents us with an enormous data processing requirement which can impede us from gaining the insights that the data have to offer. Two major approaches for dealing with this big data problem include manual analysis via citizen science and automated recognition through machine learning algorithms.

Currently, manual identification of avian species requires, on average, twice as much time as the length of the recording [6]. This is due to the fact that the participants repeatedly replay the same recording to confirm whether the species have been correctly recognized. Citizen science is one of the solutions for an efficient analysis of a huge amount of acoustic data (24TB, covering 8 years). The basic idea is to mobilize the general public to work in collaboration with the professional scientists to complete a certain task with massive data. Galaxy Zoo [7] and Whale FM [8] are good examples that use citizen science to solve their own problems. Similar experiments have been conducted in avian species annotation. The participants were asked to annotate avian species by listening to an audio recording or visual inspection of a corresponding spectrogram [9]. However, this method attempts to increase the number of participants involved in annotating the acoustic data instead of reducing the volumes of data. The accuracy of the annotations can be unreliable because domain knowledge varies from experts to non-experts [10].

An alternative approach to improve the efficiency of determining avian species richness in acoustic data is automated acoustic event detection. Most of the automated approaches focus on the recognition of a single or several species with clear vocalizations [11-14]. These techniques perform well when the original acoustic data have a high signal-to-noise ratio. However, recordings collected from the natural environment contain background noise (geophony: such as rain and wind; anthropophony: such as mechanical noise) and complicated acoustic structures (such as concurrent vocalizations). These factors will lower the accuracy of the automated recognition approach. Although multi-instance multi-label method [15] enables to detect different avian species in the recordings, it requires annotated avian species as training data.

To address the aforementioned problem, our major contribution is to introduce an assistive approach to improve the efficiency for determining different avian species. This applies whether it be citizen science, automated detection and recognition, or simply a trained ornithologist manually inspecting the data. Our method utilizes a decision tree model to classify acoustic data into five classes at a one-minute resolution. By removing the non-avian acoustic data, we successfully reduce the data to about 50% its original size and improve the efficiency about 10% for ecologists to search for avian species in one-day acoustic data.

The remainder of this paper is structured as follows. Section II overviews the related work. Section III describes the materials and method used in this study. The results are reported in section IV. Section V and VI are discussion and conclusion respectively.

II. RELATED WORK

A. Sampling Protocols for Avian Species Richness Surveys

Point count survey [16, 17] is one of traditional in-the-field sampling protocols to determine avian species richness. It requires experts to go into the field in person, writing down any species they see or hear. This manual task is time-consuming, labor-intensive and, most importantly, the result is difficult to verify. Acoustic sensors enable the continuous collection of environmental data. Now the in-the-field-observation effort becomes a big data analysis problem. Listening to all recorded data is prohibitively expensive. Although automated detection method is evolving rapidly, building a generic recognizer to detect all avian species is impractical because of variation of vocalizations and unknown species in the recordings [18].

To improve the efficiency of determining avian species richness in massive acoustic data, The paper [6] suggested a semi-automated method to determine avian species richness. They compared random sampling protocols over several different segments of time in a day and suggested that sampling three hours after dawn successfully improves the efficiency of determining avian species richness over five days' acoustic data. However, the use of this sampling protocol will miss out avian species that only vocalized outside of those three hours and it is subject to weather conditions.

B. Acoustic Indices

Recently, various acoustic indices have been proposed to scale up the analysis of massive acoustic sensor data [19]. An acoustic index summarizes the acoustic information in any arbitrary length of an audio recording. The first introduced acoustic indices include acoustic entropy index and acoustic dissimilarity index (based on Shannon theory), which aim to assess biodiversity at large temporal and spatial scales [20]. Acoustic complexity is another index that is widely used to monitor the activity of avian species and long-term ecosystem change [21].

A single index is hardly able to summarize all facets of the acoustic data. Based on the idea that combinations of acoustic indices may complement for each other in summarizing acoustic information, a weighted linear combination of acoustic indices was used to determine avian species richness of a one-day recording [22]. The combinations of five indices leaded to more efficient results than those of traditional point-count survey or random sampling of a whole day's data.

Acoustic indices have also shown promising applications for characterizing long-duration acoustic patterns [23], such as avian vocalizations and rain. In this research, we used acoustic indices to describe five common acoustic patterns in a one-day recording. Twelve acoustic indices were calculated at a one-minute resolution and used to build a decision tree model. By classifying acoustic data, we were able to exclude the non-avian minutes and search for avian species more efficiently.

In this paper, we proposed a classification approach to help ecologists for more efficient determination of avian species richness in one-day acoustic data. Acoustic indices will be used as features to build a decision tree model. 1440 minutes (One-day) acoustic data will be classified into five classes: 'Aves', 'Insects', 'Low activity', 'Rain' and 'Wind'. With the avian species annotated prior to this research, we can simulate the situations that whether ecologists will have higher efficiency in determining avian species richness when present with classified 'Aves' minutes.

III. METHOD

A. Study Sites and Data Collection

The acoustic data were collected from the Samford Ecological Research Facility (SERF) located in the northwest of Brisbane, Australia (27.39˚S, 152.88˚E). The vegetation where the recordings were taken consists of inland open-forest and woodland, more details can be found in the paper [6]. The acoustic data were collected from two sites in the SERF over six days. One recording was recorded in stereo WAV format on 13th April, 2013 and the others were recorded in stereo MP3 format (128 Kbit/s, 22.05 kHz) from 13th to 17th October 2010 [24]. All the recordings were cut into one-minute audio clips. The 1440 minutes on 15th are left out as a test dataset. There are 150 minutes selected as training data from the other five days. Three experienced experts have worked collaboratively to annotate all avian species at a one-minute resolution from 13th to 17th October 2010. These annotations are used to verify the efficiency of determining avian species richness.

B. Calculation of Acoustic Indices

In this research, 12 acoustic indices were calculated for each one-minute audio clip, either from waveform or spectrogram data. Among them, average signal amplitude, background noise features, signal-to-noise ratio, and entropy of signal envelope are generic indices for describing temporal acoustic information; while the remaining indices are able to characterize spectral information. This section briefly describes the calculation of 12 acoustic indices.

1. Average Signal Amplitude
2. Background Noise Features
3. Signal-to-noise Ratio (SNR)
4. Entropy of Signal Envelope
5. Acoustic Complexity Index (ACI)
6. LowFreqCover
7. MidFreqCover
8. HighFreqCover
9. Entropy of Average Spectrum
10. Entropy of Peaks
11. Horizontal Ridge
12. Vertical Ridge

The first four indices are calculated from time-domain audio signals. Here, an envelope refers to the maximum amplitude of a 512-point non-overlapping window over a waveform signal.

1. **AveSignalAmplitude**: It is the average amplitude of the waveform envelope. A logarithmic unit (decibel) is used in this experiment.

2. **BackgroundNoise**: It measures constant acoustic energy estimated from the waveform. It is also converted to the decibel.

3. **Signal-to-noise ratio**: It is the decibel differences between maximum amplitudes of the waveform envelope and the corresponding background noise features.

4. **Entropy of signal envelope**: It is an entropy index calculated from energy (squared amplitude) of waveform envelope.

The spectral acoustic indices are calculated from a spectrogram, where a spectrogram is the short-time Fourier transform of a waveform signal. Spectral acoustic indices include:

5. **AcousticComplexity**: It is the average absolute amplitude differences between adjacent time frames.

6-8. **FrequencyCover**: It refers to the count of values that are greater than a threshold divided by the total time frames of a spectrogram. This threshold is 3dB in this paper chosen by trial and error. Frequency cover has been divided into three frequency components (0-482 Hz, 482-3500 Hz, and 3500-8820 Hz), which are called low, mid, and high -frequency cover respectively.

9. **AveEntropySpectrum**: It is an entropy index of average amplitude calculated in each frequency bin from 482 Hz to 8820 Hz.

10. **EntropyPeaks**: It is also an entropy index of amplitude that has maximum counts in each frequency bin from 482 Hz to 8820 Hz.

11-12. **Ridge indices** (**verRidge** and **horRidge**): If a spectrogram is considered as an image comprised of pixels, ridges are local maxima in at least one dimension of a spectrogram. Reference [25] introduced ridge features for bird vocalization retrieval in massive acoustic data. Based on their ridge features, the ridge indices used in this research are the average count of vertical and horizontal ridges in a spectrogram.

C. Classification of One-day Acoustic Data

Fig. 1 is a false-color spectrogram of a 24-hour recording on 13th October 2010. It illustrates the distribution of different acoustic patterns at a one-minute resolution. Each pixel stands for a single frequency bin of a particular minute. Normalized acoustic indices such as acoustic complexity index, temporal entropy and frequency cover were assigned to RGB values to construct this figure. We can see that the majority of aves vocalized from around 5:00 to 18:00 during the day. According to the acoustic adaptation hypothesis [26], rain and wind are causes of the absence of avian vocalizations. The purpose of classification is to find the avian-active minutes. In this paper, we proposed to use a decision tree to classify minutes of a one-day recording into five classes: 'Aves', 'Insects', 'Low activity', 'Rain' and 'Wind'. These classes reveal the distribution of fundamental acoustic patterns in long-duration recordings.

The decision tree is trained by a ten-fold stratified cross validation method. This algorithm has been implemented in Weka 3.7 [27]. Fig. 2 demonstrates the five classes: 'Wind', 'Insects', 'Aves', 'Low activity' and 'Rain'. The training data consist of thirty one-minute samples for each class recorded from the SERF (on 13th, 14th, 16th, 17th October 2010 and 13th April 2013), resulting in a total of 150 minutes. The model was tested on a 1440-minute recording on 15th October 2010. Minutes classified as 'Aves' were reserved for further species richness surveys.

D. Evaluation

To evaluate the approach, a plot of accumulative avian species against the number of minute samples is drawn. Two benchmarks have been established for a one-day recording. One is the theoretical best curve derived from annotations of avian species; the other one is the baseline that sampling1000 trials at random on 1440 minutes (one-day) recording. The improved sampling result is supposed to reside between these two benchmarks. The result is considered to be better if an accumulation curve approaches the first benchmark. The 60th one-minute sample is also chosen in order to compare with the results obtained from other methods.

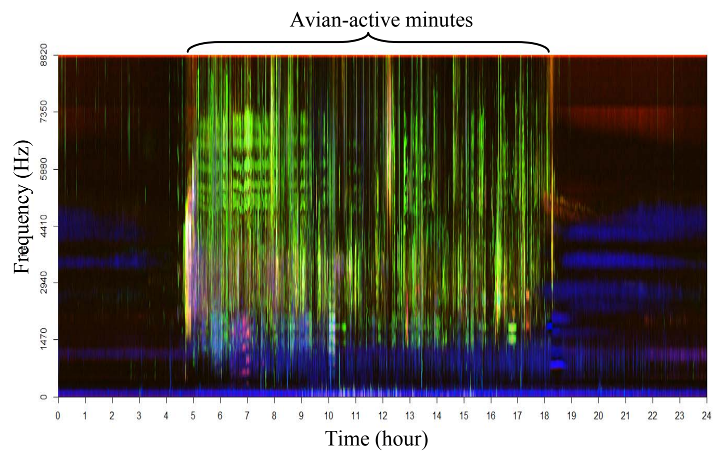


Fig. 1. Avian-active minutes of a 24-hour recording, 13th October, 2010

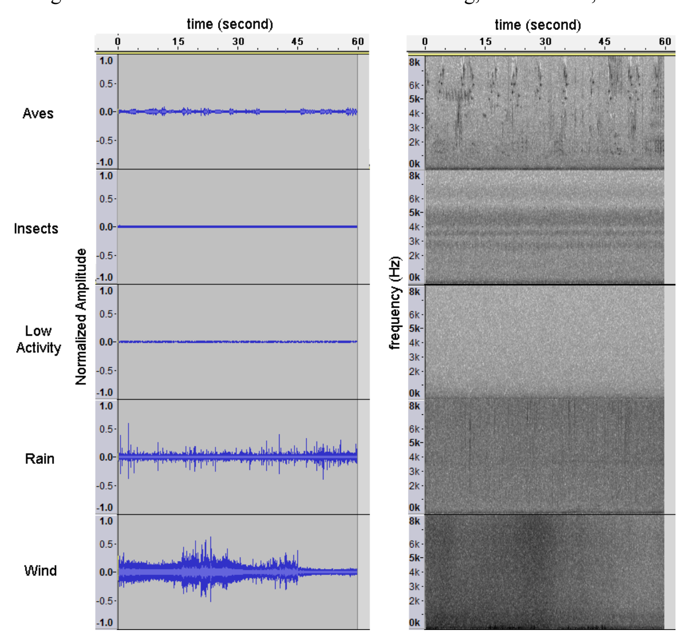


Fig. 2. Examples of five classes at a one-minute resolution (left: waveforms; right: spectrograms)

IV. RESULTS

A. Classification Accuracy

The decision tree model trained by 12 acoustic indices is shown in Fig. 3. The Gini impurity has been used as the splitting rule. A forward feature selection has been used to select the best feature set. Three acoustic indices – **horRidge**, **AcousticComplexity** and **BackgroundNoise** – were determined by the algorithm as the most important features for classifying one-minute audio-clips. The **horRidge** is capable of capturing lasting acoustic energy in a spectrogram, which is commonly found in sounds of 'Insects' and some avian vocalizations. The **AcousticComplexity** describes the relative intensity differences between adjacent time frames of a spectrogram. 'Rain' and some avian vocalizations have similar acoustic features. By contrast, 'Wind' and 'Low activity' do not have the acoustic features described above. 'Wind' is a sporadic energy burst and 'Low activity' has low acoustic energy in a one-minute audio clip, which explains why **BackgroundNoise** was chosen to discriminate these two classes.

TABLE I is the confusion matrix for the 150 training one-minute samples. The diagonal values (in bold) represent the correctly classified instances of the training data. The overall classification accuracy is 89.3%. Particularly, the class 'Insects' has the highest classification accuracy (100%) and the classification accuracy for 'Aves' is 92.9%. Notice that 'Low activity' and 'Wind' have the most misclassified instances; this is due to the fact that 'Wind' is sporadic acoustic energy, acoustic indices averaged across one-minute audio are not able to summarize enough acoustic information to discriminate them.

The results for the test dataset on 15th October 2010 are shown in TABLE II. The overall classification accuracy is 82.6% with a total of 1440 minutes. The classification precision for the class 'Aves' is 87.7%. According to the avian annotations, 93.6% (58/62) of the total avian species remain within 44.0% (634/1440) of a one-day recording. Note that the majority of misclassifications for the test dataset occurred between the 'Aves' and 'Rain'. This is mainly because some avian vocalizations have similar features as rain and, the acoustic indices used in this study fail to distinguish them. With the annotations of avian species, we know that more than half of the total amount of acoustic data can be removed without losing many species (TABLE III). The huge data reduction on 16th October is because of strong wind gusts in that day.

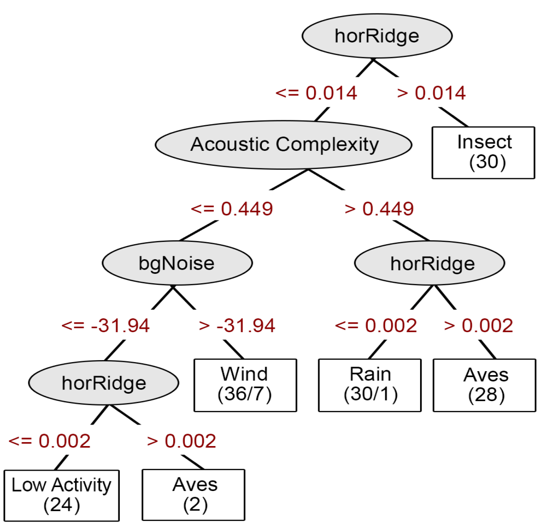


Fig. 3. The decision tree model. The oval nodes represent the features (acoustic indices) to split the training instances. Rectangular boxes represent the five classes. The left number is the total instances in that class and the right number is the misclassified instances. A single number means that they are all correctly classified.

B. Determination of Avian Species Richness

Fig. 4 shows the accumulative curves of avian species found per minute over two days. We compared the classification approach with two benchmarks. The triangles are the theoretical best results that we can achieve with the avian annotations. The baseline method is sample 1440 minutes at random. Apparently, random sampling on minutes classified as 'Aves' obtains a better result than the baseline method.

On 16th October 2010, our method has found an average of 20% more avian species after the 10th minute sample (Fig. 4). Strong wind gusted throughout the day and the avian species

TABLE I. CONFUSION MATRIX OF TRAINING DATA

Classified as →	Wind	Insects	Aves	Low activity	Rain
Wind	**27**	0	0	2	1
Insects	0	**30**	0	0	0
Aves	0	0	**28**	2	0
Low activity	7	0	1	**21**	1
Rain	1	0	1	0	**28**

TABLE II. CONFUSION MATRIX OF TEST DATA

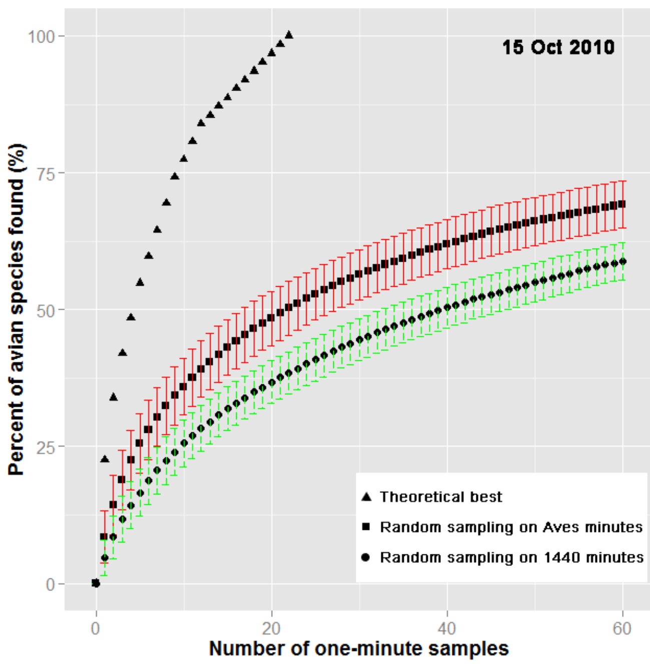
Classified as →	Wind	Insects	Aves	Low activity	Rain
Wind	**28**	0	13	17	4
Insects	0	**0**	0	0	0
Aves	4	6	**556**	31	53
Low activity	13	0	18	**359**	17
Rain	10	0	47	16	**243**

TABLE III. THE NUMBER OF AVIAN SPECIES BEFORE AND AFTER CLASSIFICATION

	October 2010				
	13th	**14th**	**15th**	**16th**	**17th**
Before	62	58	62	45	62
After	60	57	59	39	58
Data reduction	51.5%	44.6%	56.0%	87.3%	49.0%

were less active. Our classification approach successfully removed windy minutes which did not include aves but occupied much of the day, so there is a huge gap between our method and the method of random sampling on 1440 minutes.

An ANOVA was tested to see whether our classification approach is effective in improving the efficiency of determining avian species richness. Since the distribution of percent of avian species found at each minute sample is not normal (tested by Shapiro-Wilk's test, $p < 0.001$), the paired t test is not suitable for our experiment. Instead, a two-sample paired Wilcoxon (also known as Mann-Whitney) tests was used. From the results ($p < 0.001$), we can reject the hypothesis that the percent of avian species found per minute are the same by random sampling on 'Aves' minutes and a one-day recording. It also confirms that our classification approach has successfully improving the efficiency of determining avian species richness by reducing the non-avian minutes.



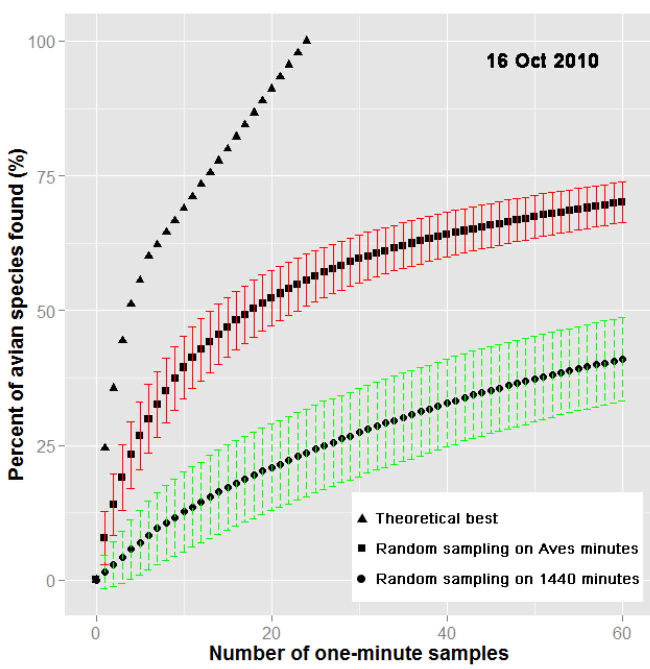


Fig. 4. Accumulative curves of avian species found per minute. The triangles and circles are the best and worst situations in determining avian species richness. Squares symbolize the results of random sampling on 'Aves' minutes. Error bars are one-standard deviations at each one-minute sample.

V. Discussion

We compared the 60th one-minute samples calculated from four different sampling methods for each of five days' acoustic data (TABLE IV). The average values showed that random sampling on 'Aves' minutes provides a 10% higher efficiency of determining avian species richness than that on a one day's recording. This is due to the fact that our classification approach reduces the volumes of the dataset while reserving the majority of unique avian species.

Our classification approach provides a result as good as the previous research but is robust under different conditions. One of the previous methods is called dawn sampling [6]. However, if rain or wind dominates that period of time, dawn sampling will hardly capture any avian species. Our method explained how the acoustic indices can be used to improve the efficiency of determining avian species richness by discriminating five fundamental patterns in acoustic data.

The missing avian species were also investigated. They were classified in non-avian minutes because the acoustic energy of their vocalizations was low and the acoustic indices were not able to capture relevant information after taking an average value of a one-minute audio clip. Take 15th October 2010 for example. Red junglefowl (Gallus.gallus) and Willie wagtail (Rhipidura.leucophrys) vocalized before dawn and their vocalizations were too faint for acoustic indices to summarize ample acoustic information, so these minutes were misclassified as 'Low activity'. Rainbow bee-eater (Merops.ornatus) was present at the 977th minute, but the vocalizations were masked by rain. Acoustic event detection can be used to deal with this single case.

VI. Conclusion

Acoustic sensors have enabled the continuous collection of acoustic data for monitoring the natural environment. However, manual analysis of such a big dataset is expensive and time-consuming. To scale up the analysis of massive acoustic data, acoustic indices and computer-assisted techniques have been introduced. This research was motivated by the use of acoustic indices in characterizing long-duration audio recordings. Using acoustic indices as features, we built a simple and robust decision tree model to classify one-minute acoustic data into five classes. After removing the non-avian minutes, we approximately reduced 50% of one-day's acoustic data, thereby improved the efficiency of determining avian species richness by 10%. This approach has the potential to reduce months' or years' acoustic data for avian species surveys.

TABLE IV. PERCENT OF AVIAN SPECIES FOUND AT THE 60TH ONE-MINUTE SAMPLE USING DIFFERENT SAMPLING PROTOCOLS

Sampling protocols	October 2010					Average
	13th	14th	15th	16th	17th	
Random sampling on a one-day recording [6]	64% ± 5%	54% ± 5%	59% ± 6%	41% ± 8%	56% ± 10%	54% ± 14%
Dawn sampling [6]	70% ± 3%	65% ± 4%	73% ± 3%	65% ± 4%	61% ± 3%	67% ± 3%
Our classification approach	71% ± 4%	65% ± 5%	69% ± 4%	69% ± 4%	61% ± 4%	67% ± 4%

This paper reports a simple but efficient classification model to reduce acoustic data for determining avian species richness. Since new acoustic indices are emerging and show a promising application in characterizing long-duration audio data, we can use them as additional information to direct the selection of Aves minutes after classification. The future work will also test the classification approach with audio collected from different locations and over a wider range of days.

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