# Analysis of morepork vocalizations recorded using a permanently located mobile phone

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## ABSTRACT

The purpose of this work included the annotation of audio recordings of bird vocalizations to be used to train a machine learning algorithm to automatically detect bird calls. In addition, this work was intended to demonstrate the ability of The Cacophony Project's mobile phone based 'Bird Monitor' for on-going monitoring of bird vocalizations. This work is important because it forms part of The Cacophony Project's strategy to provide a low cost and robust means of collecting bird vocalization information to help determine the effectiveness of pest control activities. The main results show that the Bird Monitor does reliably capture bird calls over an extended period and can be used to create many annotated recordings from a real situation. It is concluded that the approach of choosing the distinct call of the Morepork as an entry into the area of automatic bird call counting was valid.

**Keywords**: bird vocalisations, bird calls, morepork, automated recorders, automated detection, Hammond Park Hamilton

## 1. INTRODUCTION

The ability to automatically record environmental signs is becoming increasingly important as the effects of humans are more and more of concern. One aspect of worry in New Zealand is the affect that pest species have on bird life and The Cacophony Project (The Cacophony Project, n.d.) was established to rid New Zealand of these pests through the use of technology. To help establish the success or otherwise of pest eradication, the project intends to monitor bird health using a large number of audio recorders, known as 'Bird Monitors' (2040, 2019; Google, 2019). These monitors automatically make audio recordings for one minute every hour and one minute ever ten minutes for the hour before and after dawn and dusk. The recording is uploaded to a server for analysis and viewing. Figure 1 shows an intial prototype of how users can listen to a recording and note any points of interest (known as tags or annotations) at the location in the recording. Development of this interface is the subject of other work.

The ultimate aim is to be able to automatically annotate/tag the recordings with all bird calls that are present in the recording. It is also desirable to remove any recordings that contain human vocalisaitons for privacy purposes and this has been the subject of previous work (Hunt, Ryan, & Ryan-Pears, 2017) but at the time of writing we do not have a satisfactory solution in place for this issue. There are two main approaches for automatically annotating recordings using machine learning, these being supervised and unsupervised learning. The former, attempts to automatically separate sounds into 'bins' of similar type in the expectation that all items in a bin belong to the same source e.g. bird type/call. Supervised learning relies on the availability of pre tagged recordings that can be used to train the learning algorithm and it is the creation of these tags that this work is addressing.

We describe the analysis of approximately 250 hours of audio recordings from a single Cacophony Bird Monitor recorded in the 11 months between July 2018 and May 2019 in Hammond Park, Hamilton, NZ. The total length of recordings meant a completely manual approach to tagging impractical. Instead it was decided to try to automatically find places of interest and 'offer' them up to the listener in quick succession for the listener to tag.

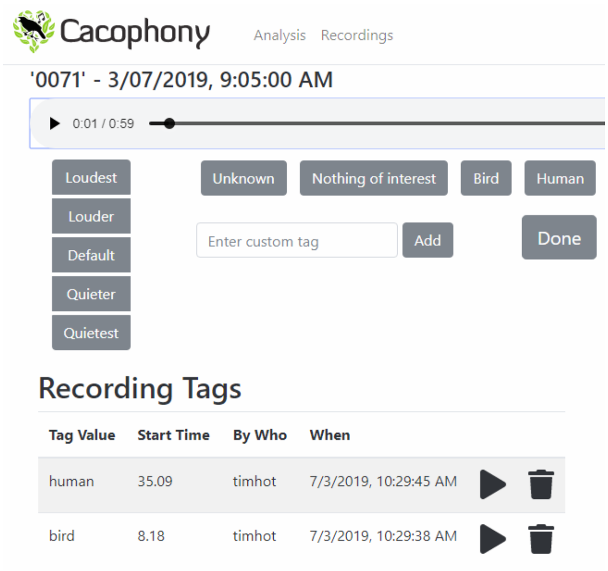


**Figure 1: This shows a prototype of how users can listen to a recording from a Bird Monitor and 'tag or annotate' the recording with any sounds of interest.**

Cursory listening to the recordings revealed the presence of the very distinctive double barrelled call of the morepork. This gave one of the authors, TH, the idea that this would probably be one of the easiest calls to tag and would also be of interest to issues of conservation. The morepork is known to only call at night, and so this would dramatically reduce the quantity of analysis that would be needed. It was also important that the person doing the actual tagging had a high confidence in correctly identifying the call.

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For the purpose of this study, and for future automatic analysis, the technique known as onset detection was used to find points in the recordings that indicate a possible start of an audio event of interest; so reducing the total number of hours that had to be manually listened to.

An initial exploratory evaluation of the detected onsets quickly determined that the percentage of onsets that were morepork calls was very low and confirmed the need to automatically eliminate as many of these as possible. Four techniques described in the Methodology section were used to do this.

In summary the purpose of analysis was:

- To create a set of annotated (tagged) recordings that will be used for the basis of training a machine learning algorithm that will in turn be used to automatically measure morepork call frequency.
- An early demonstration of the potential of using the Cacophony Bird Monitor and Cacophony infrastructure (including storage, API and web interface) to achieve a reliable estimate of bird health - especially any changes that might occur over time.

# 2. LITERATURE REVIEW

## 2.1 Invasive pests in New Zealand

New Zealand's native fauna and flora is under threat due to several reasons including introduced pest species (Department of Conservation, New Zealand Government, n.d.; Bourdôt, Kriticos, & Dodd, 2018). There are numerous initiatives to control and monitor animal pests in New Zealand for example recent work includes: aerial dropping of the poison 1080 to control possums (Vianen, Burge, MacFarlane, & Kelly, 2018), evaluation of camera monitoring (Anton, Hartley, & Wittmer, 2017) and the mapping of populations (Shepherd, et al., 2017).

## 2.2 The New Zealand morepork

Although not listed as threatened, the native New Zealand morepork (Ninox novaeseelandiae, also known as ruru, boobook, New Zealand owl) a small forest-dwelling owl (Seaton & Hyde, 2019) has been the subject of numerous studies since at least 1948 including (O'Donnell, 1980; Cunningham, 1948) to assess its presence, behaviour and abundance in several locations throughout New Zealand. The morepork has a range of calls (New Zealand Birds Online, 2013) of which the most recognizable a distinct 'more-pork' sound, also referred to as a 'quork-quork' or 'hoot', might be one of the reasons for the interest in its population status. Indeed, this work selected the morepork to study due to this call. Calls may be grouped by function including contact/separation, alarm, food sharing, begging and aggressive (Brighten, 2015). They identified eleven call types in total and named as "more-pork, more-more-pork, rororo, trill, low trill, weow, copulation squeal, juvenile chicketting call, chick trill, distress squeak and single hoot". They also noted that unlike other studies, they heard calls during the day on several occasions and suggest it was due to disturbance by the human observer.

The city of Hamilton, New Zealand has few remaining areas of native vegetation (Clarkson & McQueen, 2004) yet moreporks are known to exist there and manual surveys by human volunteers verified their presence in 11 sites (Morgan & Styche, 2012) including the gully section known as Hammond Bush, adjacent to the Waikato river which was used in this current study. The authors noted that "ruru vocalisations are easily recognisable, meaning that a high degree of ornithological experience was not necessary in order for people to be involved…". Surveys were conducted in the month of October based on observations of morepork in Australia (Olsen, Trost, & Hayes, 2002) that reported that October had the highest reported nights of observation. However other authors (Colbourne & Digby, 2018) have noted that the months of maximum observation appear to be variable from location to location but did observe a reduction of calling rates in March which they suggest corresponds to when chicks have fully fledged. They also observed the inconsistent reporting of when moreporks are most active with respect to time of night but did observe a reduction in observed calls during times of strong wind and moderate to heavy rain. They concluded that concentrating on the 'hoot' (more-pork) call may be cost-effective due to the ability to detect it during light rain and because it is by far the most prevalent of the morepork calls.

The morepork breeds in spring and summer (New Zealand Birds Online, 2013) and during this time the male morepork hunts for the female around dusk and calls several times when bringing food to the nest (New Zealand Geographic, n.d.).

A recent study (Hadden, Bowie, & Pryde, 2017) using recorders, rather than humans to assess morepork activity noted that passive recorders were less likely to alter the "normal activity" of moreporks. The survey was limited to the months of December and January due to resource constraints and recorders were only placed at each site for 14 days.

The increase use and importance of automatic acoustic recorders has motivated research to determine the effects of the environment on the ability to accurately assess bird life (Priyadarshani, Castro, & Marsland, 2017). They used pre-recorded examples of birds including that of the morepork and measured the effect of variables such as day versus night, level of vegetation cover, height and distance of the audio source, wind and direction.

## 2.3 Automatic analysis of recordings

The use of recorders has enabled and resulted in many hours of recording available for analysis. It has been estimated that it can take an expert twice as long as the actual recording duration to properly analyse the recordings. This has probably led to the interest in automatically analysing the recordings. The work in this area takes the lead from other areas of audio analysis and the research has focused on the need to detect the start or onset of a sound and then the identification of that sound.

An overview of onset detection (Bello, et al., 2005) included an analysis of what it is, as well as presenting the different methods used in detecting onsets. They describe the steps involved as: pre-processing of the signal (which includes selection of frequencies of interest), reduction (which results in identifiable features such as local maxima) and finally peak-picking to estimate the onset times. Each of these areas are the subject of much research.

In other work (Lostanlen, Salamon, Farnsworth, Kelling, & Bello, 2019) improvements have been proposed to the current state of the art in bird call detection using convolutional neural networks, by the addition of 'per-channel energy normalization in the time-frequency domain' and also the modification of the neural network by replacing the 'last dense layer in the network by a context-adaptive neural network layer'. They have made their code available for others to use, including a pre-trained network that can detect warbler, thrushes and sparrows.

# 3. MATERIALS AND METHODS

A Cacophony Bird Monitor had been recording in Hammond Park (Bush) since June 2018. It is located on the side of a fern tree – see Figure 2 and is powered by a solar panel and connects to the internet using a mobile connection for automatic uploading of recordings to the Cacophony server.

The Cacophony project is an open source project and where possible also chooses to utilize open source tools. The open source Python programming language (Python Software Foundation, n.d.) was chosen as it has a very large support base in the field of audio analysis including integration with state-of-the-art machine learning platforms such as Nvidia graphics cards (NVIDA, 2019), Tensorflow (Google Inc, n.d.) and Keras software (Keras: The Python Deep Learning library, n.d.). The Spyder development environment (The Spyder Website Contributors, 2018) and Anaconda platform (Anaconda Inc, 2019) were the main development environments used.

**Figure 2: This shows the physical location of the Cacophony Bird Monitor that was used to capture the recordings for this work. The Bird Monitor is inside a waterproof box behind the solar panel that can be seen attached to a fern tree.**

As mentioned in the introduction section, it was decided to first tackle the 'low hanging fruit' of just counting the moreporks' classic more-pork call. This was done for a number of reasons including: 1) manual analysis of many recordings had already confirmed that these calls were being captured in large enough quantities to give meaningful results, 2) one of the authors, TH, was confident that they could personally identity the call with a high confidence level, 3) it was envisaged that the double-barreled nature of the call could also be used to automatically reduce the number of potential events in the recordings that would need to be manually listened to for identification.

A small Python program was written to download recordings from The Cacophony Project's API interface (The Cacophony Project, n.d.). One of the authors, CB, implemented a segmentation algorithm that finds the transitions in the waveform data where the signal changes from almost always having an amplitude less than 20% of the maximum signal strength, and regions where the amplitude is sometimes greater than 20% of the maximum. Once the transitions have been identified, we preserve only the loud segments which are longer than 1/20th of a second in duration for further analysis.

This onset detection algorithm was applied to each recording to find locations of interest. To reduce the number of onsets that had to be manually assessed, several steps were employed:

- Only recordings made between dusk and dawn were analysed.
- The sound frequency of the morepork call was established (using Audacity) to be in the frequency range of 800 to 1,000 Hz and a bandpass filter was applied to the recordings so that only those frequencies would be analysed.
- The time between the two distinct parts of the double-barrelled call was measured to be approximately 0.6 seconds. The total number of onsets to be manually analysed was reduced by picking the first onset of a pair of onsets that occurred within 0.8 seconds of each other.
- Recordings that had greater than 20 detected paired onsets, were found to often be the result of non-morepork causes such as: rain, wind or the algorithm creating onsets from background noise due to the absence of any actual audio event. Although there was a risk of missing recordings with a high number of morepork calls, all paired onsets from these recordings were discarded.

A Python program was written, and for each onset in turn it: a) played the frequency filtered audio, b) displayed a volume intensity versus time plot and c) displayed a frequency plot. A simple user interface was used to allow the user to press a button to indicate if they thought the recording was of a morepork or not. The user could also choose to play the original unfiltered recording as it was found that the filtered recording sometimes made it harder to determine what was being played. Due to the large number of recordings to be listened to, this step was performed as quickly as possible. It was decided that it was preferable to wrongly categorize a morepork as not, than to categorize a non-morepork as a morepork. This was because the primary aim of this work was to create useful annotations for input to machine learning. This caution will mean that the total number of morepork vocalizations is likely to be higher than measured, but this is not of primary concern as it is the trend in calls that is of interest. To further explain this, the absolute number of vocalizations detected will depend on a variety of parameters, for example a more sensitive microphone would give a different result.

# 4. RESULTS

## 4.1 Reduction of data

13,291 recordings were made in the period from 1 July 2018 to 31 May 2019. Table 1 shows the progression in application of the data reduction steps described in the Methodology section.

## 4.2 Human analysis

As described in the Materials and Methods section, the paired onsets were then used to manually determine if they represented a morepork call or not. This step was performed on a slightly larger (13,026 paired onsets) than that shown in Table 1. The analysis took approximately 9 hours or approximately 2.5 seconds for each onset pair.

## 4.3 Frequency plots

Figure 3 displays the distribution by month of the quantity of night-time recordings. As to be expected it can be seen that the number of night-time recordings is lower in the summer months due to the shorter nights. The number of recordings taken each month is used later in the analysis to normalize the number of morepork detections.

Of primary interest was to see if the number of morepork calls changed throughout the year. A total of 1,788 calls were discovered, but before plotting this, the data was scaled using the actual number of recordings that took place in each month. This inherently took care of the different lengths of night between the seasons and the different number of days in each month. Figure 4 shows that the number of calls does seem to change and has a correlation with the time of year when chicks are being raised.

**Table 1: Reduction of onsets at each step**

| Step | Procedure | Number of onsets | % step decrease | % of initial remaining |
|---|---|---|---|---|
| Directly from onset detection algorithm | Algorithm returns an onset if signal rises above a threshold. | 279,973 | n/a | 100 |
| Night-time only | Only keep onsets from recordings made between dusk and dawn | 127,384 | 55 | 45 |
| Band-pass filter | Apply band-pass filter to records and re-calculate onsets | 106,108 | 17 | 38 |
| Pair pick | Exclude onsets that do not occur within 0.8 secs | 64,361 | 39 | 23 |
| Eliminate high count | Recordings that had more than 20 pairs of onsets were eliminated | 11,868 | 82 | 4 |

The next analysis looked at the time (hour) when moreporks call. From Figure 5 it can clearly be seen that the frequency of calls is comparatively high in the hours just after dusk and start to decline in the 3rd hour. It should be remembered that the recordings before dusk were not analysed. A total of 657 calls have been normalized to allow for the fact that: 1) the recording frequency is higher in hour 0 after dusk than the other hours and 2) as the length of night shortens, there are fewer recordings considered to be relative to dusk from hour 3 onwards, due to those recordings being attributed to being relative to dawn.

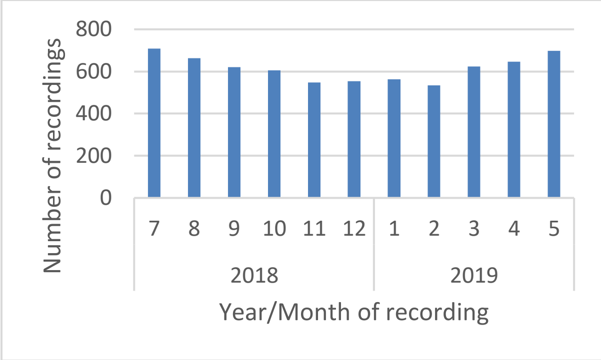


**Figure 3 : The total number of recordings made each month, showing the effect of night length on the number of recordings made.**

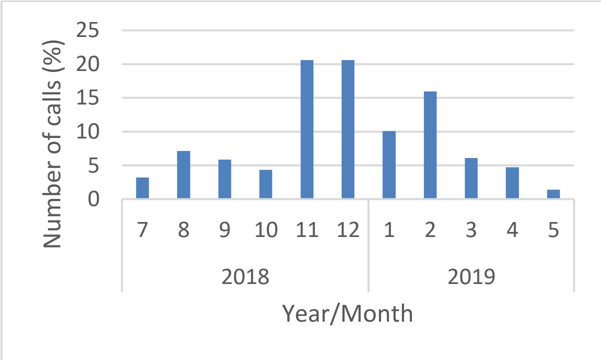


**Figure 4: Number of morepork calls per month. The obvious increase in calls in November seems to correlate with when chicks are being reared.**

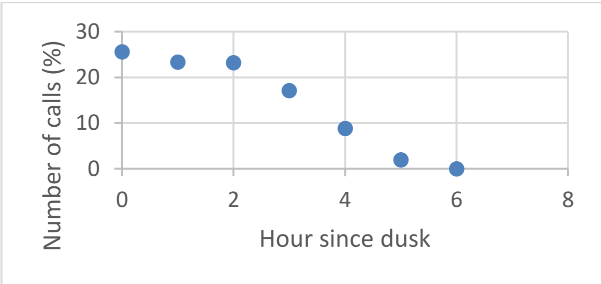


**Figure 5: This shows the frequency of calls versus the hour that they occurred since dusk.**

The frequency of calls (a total of 1,148 and normalized for quantity of recordings) in the hours before dawn were also analysed (Figure 6) although no obvious trend could be determined.

## 4.4 Creation of Tags for training Machine Learning Algorithm

Once the final stage of data reduction was completed, a python program was written and used to create 1,788 tags on the Cacophony server using the API mentioned previously. Figure 7 gives an example of what a user will see and shows how they can easily step through the tags which were labelled as 'more pork – classic'.

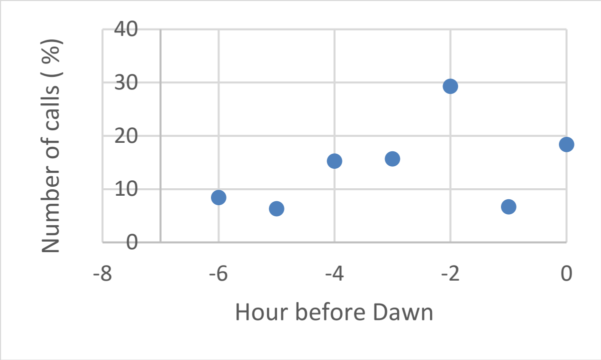


**Figure 6: This shows the number of detected morepork calls in the hours preceding dawn. Unlike the result for dusk, no discernible trend is observed.**

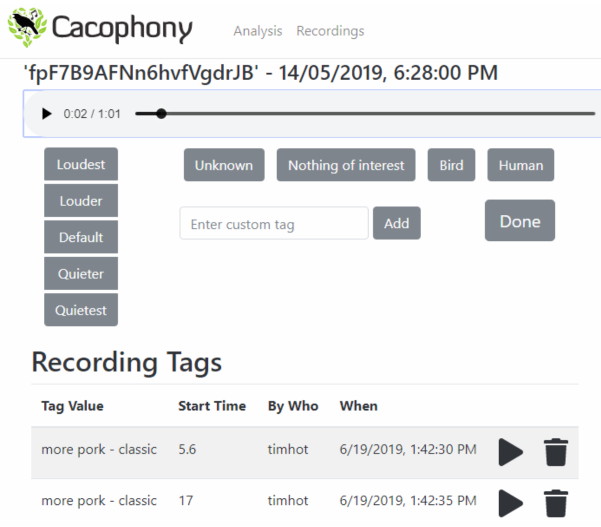


**Figure 7: The user interface showing the 'more pork – classic' tags at the bottom. Users can press the 'play' button for each tag to listen to the corresponding part in the recording.**

All the morepork annotations/tags are now available to use for further analysis and for training an algorithm for automatic detection.

## 4.5 Evaluation

As the manual categorisation was done with some haste, it is likely that some of the paired-onsets were incorrectly categorized. To get an estimate of the accuracy, a selection of recordings (one from each month, eleven in total) were listened to using Audacity. The Audacity effects of amplification and low and high pass filters were also used.

**Table 2: Annotation accuracy**

| | |
|---|---|
| Number of tags created. | 60 |
| Number confirmed to be correct. | 53 |
| False positive rate. | 13% |
| Number of vocalisations missed | 45 |
| False negative rate | 46% |

Of the seven false positives, five were from a single recording and even after listening to the recording multiple times, the author could not be certain that they were due to a morepork and so were labelled as not.

# 5. DISCUSSION AND CONCLUSION

This work has successfully demonstrated the creation of a set of annotated/tagged recordings for the future development of a machine learning algorithm for automated analysis of bird vocalisations and has also shown that a Cacophony Bird Monitor can reliably capture recordings over an extended period. The semi-automated approach combined with concentrating on the more-pork call, meant that the quantity of onsets that had to be listened to was only 4% of those originally identified by the onset detection algorithm.

To assess the accuracy of the annotations, a sample of the annotations were carefully checked. In one of the recordings, it was found that five calls may have been incorrectly tagged. However even after listening to the calls multiple times this could not be accurately determined and so the reported false positive rate of 13% may in fact be much lower. The number of missed vocalisations, the false negative rate of 46% was disappointingly high, but is probably due to the deliberate strategy to err on the side of caution and not create too many false positives. The technique of ignoring recordings with more than 20 detected-paired onsets may also mean that the number of false negatives could be higher.

The frequency of calls in the area of study, was found to be highest in the months of November and December and shows that previous work (Morgan & Styche, 2012) that assumed the highest calling would be in October may have been incorrect. This fits with other studies (Colbourne & Digby, 2018) that suggest that the month of maximum vocalisations varies from location to location.

Our observation of frequency of calls during the night (Figures 5 and 6) indicate a slow decline in the hours following dusk which is in contrast to the peak in frequency at three hours after sunset observed by Colbourne and Digby (2018). However, they also observed a second peak two hours before dawn which does seem to correlate with our findings.

The use of automated recorders has led to a substantial increase in the quantity of recordings that need to be analysed and many groups are working on solving the issues of automated detection of bird calls. It is envisaged that implementation of many of the current state of the art techniques in conjunction with the annotations created in this work will result in the creation of an accurate automatic morepork vocalisation detector and lessons learnt will support the creation of further specific call detectors.

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