TECHNICAL REPORT

Title: The Clustering of Acoustic Indices derived from Long-duration Recordings of the Environment.

Author: Yvonne Phillips and Michael Towsey

y.phillips@hdr.qut.edu.au. m.towsey@qut.edu.au

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Institution: **QUT Ecoacoustics Research Group | www.ecosounds.org**

Science and Engineering Faculty,
Queensland University of Technology,
Brisbane, Australia

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This paper outlines the recording dataset and methods used to choose a clustering algorithm for a large twenty-six month acoustic dataset. The recordings were of the natural environment and consist of thirteen months of recording from each of two sites in two national parks 160 km north of Brisbane, Queensland. This paper also explains the calculation and use of the intra-three-day-distance (I3DD) error measure used to determine the optimum clustering result. Site maps and photos are provided at the end of this document.

Site Description

The two recording sites were at Gympie National Park (26° 3'S, 152° 42' E), elevation 225 m and Woondum National Park (26° 16' S, 152° 47' E), elevation 118 m. Recording commenced at both sites on the 22 June 2015 and continued until the 23 July 2016 inclusive. Both sites are Eucalypt woodland, located about 160 km north of Brisbane. The Gympie National Park site is a Spotted Gum (Corymbia citriodora subspecies variegata) and Grey Gum (Eucalyptus propinqua) woodland. The Woondum National Park site is closer to the coast and receives a higher rainfall. Consequently, its canopy is less open. Dominant species are Gympie Messmate (E. cloeziana), Pink Bloodwood (C. intermedia) and Grey Gum (E. propinqua) and bordered by Flooded Gum (E. grandis). Both sites support resident and migrant birds including many nectar and insect feeders. The Gympie National Park site has large birds including the Australian Magpie (*Cracticus tibicen*), Pied Currawong (*Strepera graculina*) and species of owl. The Woondum sites supports more fruit eaters.

Data Acquisition

Song Meter (SM2+) recorders were used with a continuous schedule and a sample rate of 22050 Hz. Files were saved in stereo 16-bit WAVE format. Each recorder was wired to a tree at 1.5 m with two omnidirectional microphones attached directly to each meter. Batteries were changed weekly resulting in some loss of minutes. To maintain the time scale for visualization the missing minutes were inserted as zeros. For analysis and clustering these minutes were removed. There was a total of 773 missing minutes, 241 due to battery changes and 532 due to two corrupt files.

The Summary Indices

The recordings were divided into one-minute non-overlapping segments yielding a total of 1,141,147 segments. Acoustic indices were calculated on one-channel only, due to occasional microphone problems. We calculated twelve summary acoustic indices for each one-minute segment. A brief description of each index is given below. More detail can be obtained from (Towsey, 2017).

The first four indices are derived from the waveform envelope converted to decibels.

1. *Background Noise* (BGN): Calculated as described in Towsey (2017).

2. *Signal to Noise Ratio*: Obtained by subtracting the BGN value (summary index 1) from the maximum decibel value in the waveform envelope (Towsey, 2017).

3. *Activity*: The fraction of frames whose decibel value exceeds a threshold of 3 dB above the value of BGN.

4. *Events per Second*: The number of times per second (averaged over 60 seconds) that the waveform envelope crosses a threshold, θ, from below to above, where θ = BGN + 3 dB.

The following three indices (5, 6 and 7) compare acoustic energy in the low, middle and high frequency bands of the decibel spectrogram. The mid-band frequency bounds were chosen to capture most of the bird vocalisations but avoid much of the anthropophony predominant at low frequencies. Insect vocalisations predominate in the high frequency band.

5. *Low-frequency Cover* (LFC): The fraction of spectrogram cells that exceed 3 dB in the low frequency band (< 1000 Hz) of the noise reduced spectrogram.

6. Mid-frequency Cover: As for LFC but in the mid frequency band (1000 - 8000 Hz)

7. High-frequency Cover: As for LFC but in the high frequency band (8000 – 10982 Hz).

The following three indices (8, 9 and 10) describe the spectral distribution of acoustic energy in the one-minute recording segment. They are similar in purpose to the Gini index used for example in Briggs et al. (2012) to describe energy distribution within acoustic events.

8. Entropy of Peaks Spectrum: A measure of the dispersal of spectral maxima across the frequency range of 1000-8000 Hz..

9. Entropy of Average Spectrum: Equivalent to the entropy of the power density spectrum derived from a one-minute recording.

10. Entropy of the spectrum of Coefficient of Variation: The Entropy of the spectrum derived from the ratio of the standard deviation and mean of the spectral power in each frequency bin.

Indices 11 and 12 are 'ecological indices' which attempt an acoustic measure of species richness.

11. Acoustic Complexity Index (ACI): this summary index is obtained by averaging the 256 values of the corresponding spectral index (Farina, Pieretti, & Morganti, 2013; Pieretti, Farina, & Morri, 2011). It is widely used as a measure of biophony in environmental recordings. Unfortunately, it is also highly sensitive to some non-biological sound sources, such as rain. Normal practice in ecological studies is to manually exclude recordings containing rain and wind. However, in this study, the visualization of wind and rain in a soundscape is also important.

12. Cluster Count: The number of distinct spectral clusters in a one-minute segment of recording. Calculated as described in Towsey (2017). This index is an attempt to measure the degree of internal acoustic structure within a one-minute recording. It is expected that greater vocal diversity will increase the spectral cluster count.

We did trial other summary indices but found that they were highly correlated with at least one of the above twelve indices (R^2 > 0.7). No pair of the above twelve summary indices was correlated above the 0.7 threshold.

Choosing a clustering method

When comparing clustering algorithms or optimum parameter values, it is necessary to have some performance criterion with which to make the comparison. Typically, the optimum parameter values for clustering are determined by an index, such as the Dunn Index (Dunn, 1974) or the Silhouette index (Rousseeuw, 1987), which measures the discreteness and tightness of the resulting cluster set. (Higher values for these indices indicate better, i.e. more discrete, clusters.)

When we used these indices to determine the optimum number of clusters, the results were ambiguous. For example, when attempting to cluster the entire dataset of 1,141,147 12-element acoustic feature vectors using a hybrid clustering technique (to be described below), the Dunn index indicated that the optimum number of clusters would be 5 or 80 (Fig 1, left). By contrast, the Silhouette index implied that the data could not be well clustered (Fig 1, right). The maximum Silhouette value of 0.14 at five clusters was well below the 0.25 threshold, which is usually interpreted as indicating "no substantial structure" in the data (Kononenko & Kukar, 2007 p. 343). Lamirel (2016) demonstrated that many of the well known cluster validity indices including the Dunn and Silhouette indices.

The Dunn and Silhouette indices were calculated on the clusters obtained from step 1 and 2 of the three step clustering described in "The Algorithms" section. The Dunn Index was calculated using the *clv.Dunn* function in the R "clv" package (Nieweglowski, 2013). Where, the intra-cluster diameter (complete) represents the maximum distance between any two objects within the cluster. The inter-cluster distance (single) is the minimum distance between two objects belonging to two different clusters. The Silhouette index was calculated using the *distcritmulti* function in the R "fpc" package (Hennig, 2014).

Lamirel (2016) tested the Dunn and Silhouette indices on baseline datasets and found these and other validity indices had low-rates of correct prediction of the actual number of clusters. Lord, Willems, Lapointe, and Makarenkov (2017) also showed the Silhouette index gave predictions that were not

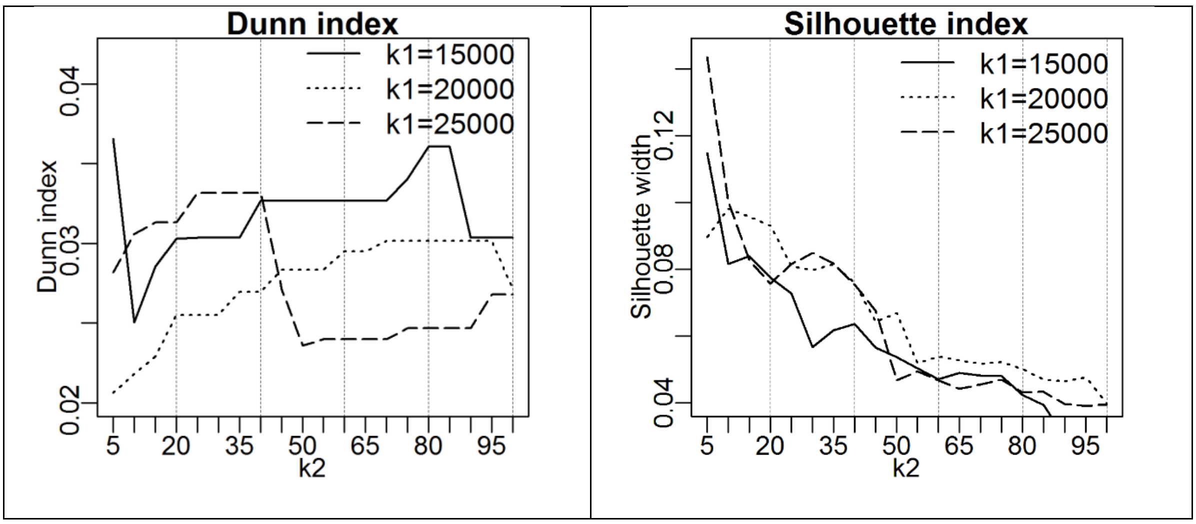

Fig 1: Graphs of cluster 'integrity' against two clustering parameters, k1 and k2. Note that k2 represents the final number of clusters. The Dunn index indicates that the optimum number of clusters is either 5 or 80. The maximum value of the silhouette index (0.14) indicates that there is no structure in the data to cluster.

well matched with the established number of clusters in the tested datasets.

Due to the ambiguity of the Dunn and Silhouette indices, we turned to the formulation of an error function based on *acoustic signatures* of 24-hour recordings that contain maximum biophony. It should be noted that the Dunn and Silhouette indices are ecologically agnostic. Consequently, we implemented an 'error' index that quantified how well a cluster set partitioned the biophony in a set of recordings. Our goal was to achieve a clustering result that maximised useful ecological information.

Our approach to this problem rests on two assumptions:

1. That the biophony of two days (rain and wind free) will be more similar, the closer their recordings are in time and space. Conversely, changes in vocal species (and therefore in biophony) will accumulate with increasing seasonal and landscape separation.
2. That *acoustic signatures* (calculated according to the method in Sankupellay, Towsey, Truskinger, and Roe (2015) of days having similar biophony will be closer than the acoustic signatures of days having dissimilar biophony. An acoustic signature derived from a set of *N* clusters is an *N*-bar histogram, each bar of which is the count of the number of times that acoustic state or cluster occurs within the 24-hour day.

These two assumptions are based on the results of Sankupellay et al. (2015), although they use the term *acoustic fingerprint* rather than acoustic signature. They found that 24-hour acoustic signatures from the same site and time-of-year are more similar than acoustic signatures from different sites and different times of year.

To make use of this result, we selected six days of recording from each of the two sites (Table 1). The days were carefully chosen to be wind and rain free, that is, to maximize the content of biophony. And we wanted the six days at each site to be grouped into two sets of three days, separated by 30 days. Note that to find 12 days which satisfied the above criteria was made much easier by inspecting false-colour spectrograms prepared as described in (Towsey et al., 2014). Finding the 12 days by listening would not have been feasible otherwise. It should be noted that the two sites (Gympie and Woondum) are only 25 kilometres apart and they contain many common vocalising species. The relatively small ecological and seasonal separation between the 3-day groups was designed to increase the difficulty of the optimisation task. Note also, that days 6 and 12 in Table 1 were not quite sequential due to the intervention of two days of rain and/or wind.

Table 1. Summary of twelve-day dataset, 6 days from each of the two sites

	Gympie NP site	**Woondum NP site**
Mid-winter	30 July 2015 (day 1) 31 July 2015 (day 2) 1 Aug 2015 (day 3)	30 July 2015 (day 7) 31 July 2015 (day 8) 1 Aug 2015 (day 9)
Early-spring	31 Aug 2015 (day 4) 1 Sept 2015 (day 5) 4 Sept 2015 (day 6)	31 Aug 2015 (day 10) 1 Sept 2015 (day 11) 4 Sept 2015 (day 12)

The ability of a clustering result to separate these 12 days into four groups of three days became our measure of clustering "error" and was used to optimize the values of k1 and k2. For a given clustering result that produces N clusters, each of the 12 days in Table 1 was converted to an acoustic signature (normalized N-bar histogram). These twelve acoustic signatures were then clustered hierarchically (using *hclust* in the R stats package (R Core Team, 2016), distance metric = ward.D2) to produce a 12-leaf dendrogram.

Ideally, a clustering run should produce clusters (and subsequent acoustic signatures) that divide the 12 days into four groups of three. We derived an error index, the intra-three-day-distance (I3DD), which quantifies the extent to which the dendrogram grouping of days departs from the 'ideal' grouping shown in Table 1. To calculate I3DD, we find the average of the maximum heights linking pairs within a three-day group using dendrograms such as Fig 2.

Given a set of *N* cluster centroids derived from one of the above four clustering algorithms, an acoustic signature is calculated for each of the twelve days. These twelve acoustic signatures are then clustered hierarchically (using *hclust* in the R *stats* package, distance metric = ward.D2) to produce a twelve-leaf dendrogram as shown in Fig 2.

From each dendrogram (derived from a single clustering run for a fixed value of *k*), we calculated a new error index, which we refer to as the intra-three-day distance (I3DD). I3DD is a measure of total intra-group integrity, that is, how far the dendrogram differs from the expected 'ideal' dendrogram, which would consist of four groups of three days: days 1, 2, 3; days 4, 5, 6; days 7, 8, 9; and days 10, 11, 12. For each three-day group, we calculated the average of the maximum of the three heights separating the pairs of group members. For example, in Fig 2, the I3DD value for the group of days 7, 8, 9 is (131 + 86)/2 = 108.5. Likewise, the I3DD value for days 10, 11, 12 is (240 + 1508)/2 = 874. And for days 1, 2, 3, I3DD = 362 and for days 4, 5, 6, I3DD = 547.5. The sum of the four I3DD values is normalised by dividing by the height of the highest node, in this case 1508, yielding a composite I3DD value of (362+547.5+108.5+874)/1508 = 1.26 for the entire dendrogram. This composite I3DD value is an 'error' in the sense that it measures the degree to which the dendrogram branches differ from the 'ideal' four branches as described above.

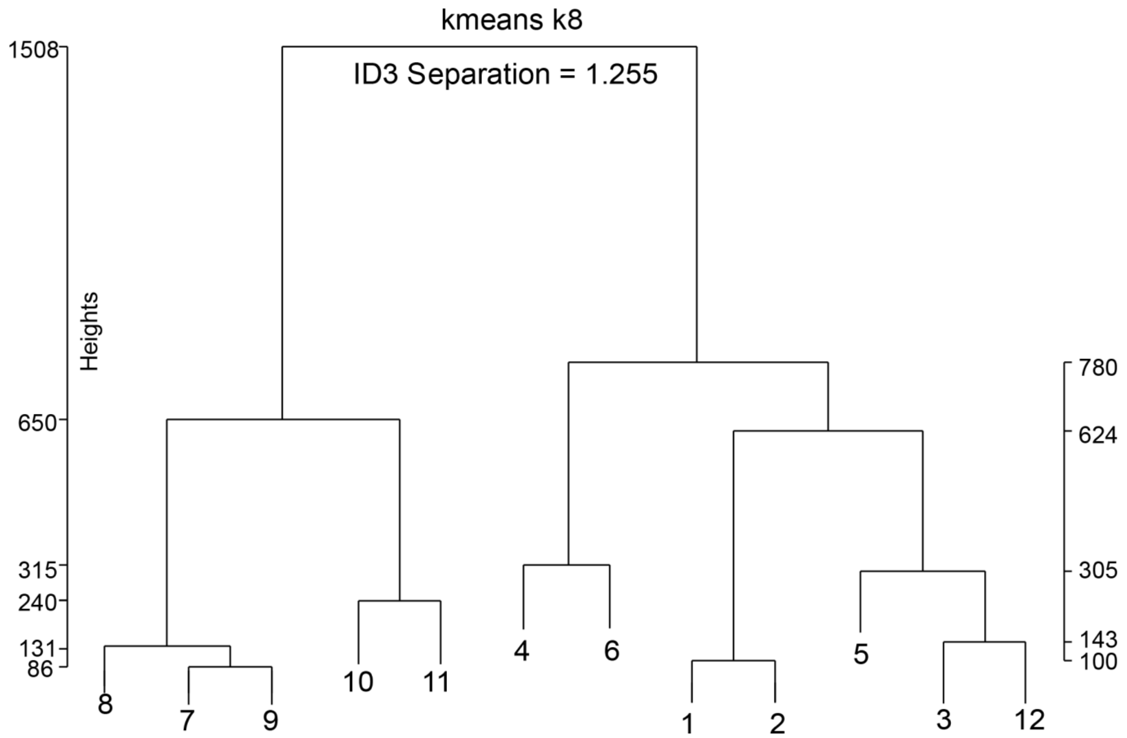

Fig 2. Example of a dendrogram derived from clustering 12 acoustic signatures obtained after clustering the 12-day dataset using *k-means*, k= 8.

Our expectation is that smaller values of I3DD will be obtained when the clusters (from which the I3DD value is derived) have partitioned the dominant sources of biophony in the 12-day data set. The achievement of a minimum quantisation 'error' is not the only criterion for selecting a clustering method. We also require that the method should not be highly sensitive to small changes in optimum parameter values and that the method should scale.

Experiment 1: Comparing four clustering methods

The Dataset

The dataset for experiment 1 was derived from the 12 days of recording in table 1. This resulted in 17280 vectors of acoustic indices, one vector per minute. After removing one of each pair of indices having a Pearson's correlation greater than 0.7, we retained seven indices per feature vector: Background Noise (BGN), Signal to Noise Ratio (SNR), Events per second (EVN), Low Frequency Cover (LFC), Acoustic Complexity (ACI), Entropy of Peaks Spectrum (EPS) and Entropy of Coefficient of Variation (ECV). The values for each index were normalised between the 2nd and 98th percentiles.

The Algorithms

The following four clustering algorithms were applied to the twelve-day dataset:

1. Algorithm 1. K-means clustering using *kmeans* in the R stats package (R Core Team, 2016) using k values of 5, 10, 15, 20, 25 and 30. An advantage of k-means clustering is that it scales to large datasets. A disadvantage is that it produces different results depending on how the cluster seeds are chosen.
2. Algorithm 2. Hierarchical clustering using *hclust* in the R *stats* package (R Core Team, 2016) using the average and ward.D2 methods for comparison. This method produced a 17280 leaf dendrogram, which was cut at the heights of 5, 10, 15, 20, 25 and 30 using the *cutree* function (Becker, Chambers, & Wilks, 1988). An advantage of Hierarchical clustering is that it is deterministic (after choice of the distance metric). A disadvantage is that the algorithm typically requires holding the entire data set in memory which does not scale to very large datasets.
3. Algorithm 3. Model-based clustering using *Mclust* in the R *mclust* package (Fraley, Raftery, Murphy, & Scrucca, 2012). *Mclust* uses the Bayesian Information Criterion (BIC, closely related to the Akaike Information Criterion) to select a single optimal cluster model from a finite set of models. BIC balances error minimisation (more clusters reduce error) with model complexity (more clusters increases complexity). We calculated the BIC for 1-50 clusters.
4. Algorithm 4. A hybrid clustering method which combines *k-means* partitioning and *hierarchical* clustering. This method attempts to take advantage of the best aspects the *k*-means and hierarchical algorithms: *k*-means is fast and can be used on large datasets; hierarchical clustering does not scale well but is deterministic once a distance metric is selected. The hybrid method consists of three steps:

   Step 1: Partition the total dataset into a large number ($k1$) of clusters using *k-means*. For the twelve day dataset we used values of $k1$ from 2000 to 4000 in steps of 500, these values increase with the size of the dataset, the values used for the 26 month dataset (given later in the paper).

   Step 2: Cluster the $k1$ cluster-centroids (from step 1) using hierarchical clustering, cutting the tree using values of $k2$ ranging from 10 to 100 in steps of 5.

   Step 3: Assign each minute in the dataset to one of the $k2$ clusters from step 2 using *knn* (*k*-nearest-neighbour) in the R *class* package (Venables & Ripley, 2002) where the number of neighbours considered is the square root of k2 (Lantz, 2015).

Optimising parameter values

Algorithms 1 and 2 require the parameter *k* (cluster number) to be optimised and Algorithm 4 has parameters $k1$ and $k2$ that need optimisation. Typically, the optimum value of *k* is determined by some measure of quantisation error, which declines as *k* increases. An optimal *k* value would be expected to coincide with a sharp decrease in quantisation error. Unfortunately, in our case the quantisation error (measured in several ways) declined gradually and did not reveal obvious choices for a value of *k*. we therefore used the measure of I3DD described above to determine the optimum parameter values.

In the case of algorithm 3, there are no parameters to optimise because the optimum number of clusters is incorporated into the BIC. However, we use the I3DD criterion to compare the BIC result with the other three algorithms.

Results

A comparison of the I3DD 'error' curves in Fig 3a, indicates that the optimum number of clusters for the 12-day dataset (Table 1) is close to 10 for all three methods. However, k-means achieved a lower error than both hierarchical methods. The single result obtained from model-based clustering produced 39 clusters (an ellipsoidal model with variable cluster volumes, shapes and orientations - VVV) and an I3DD 'error' of 1.8 (result not shown in Fig 3a). Due to this relatively high value for minimum I3DD (the highest of all the four clustering methods) and due to its long computation time, we decided not to give this method further consideration.

Conclusion

The lowest I3DD error and corresponding number of clusters was similar for both the hybrid and *k*-means methods (Figs 3a and 3b). When the criteria of low sensitivity to small changes in the k1 and k2 values is applied we observe that although the minimum I3DD value for hybrid and k-means clustering is similar, the range of k-values over which this minimum is achieved is much broader for the hybrid method and the hybrid method scales. Consequently, the hybrid algorithm (Algorithm 4) was chosen for clustering the large 26-month dataset.

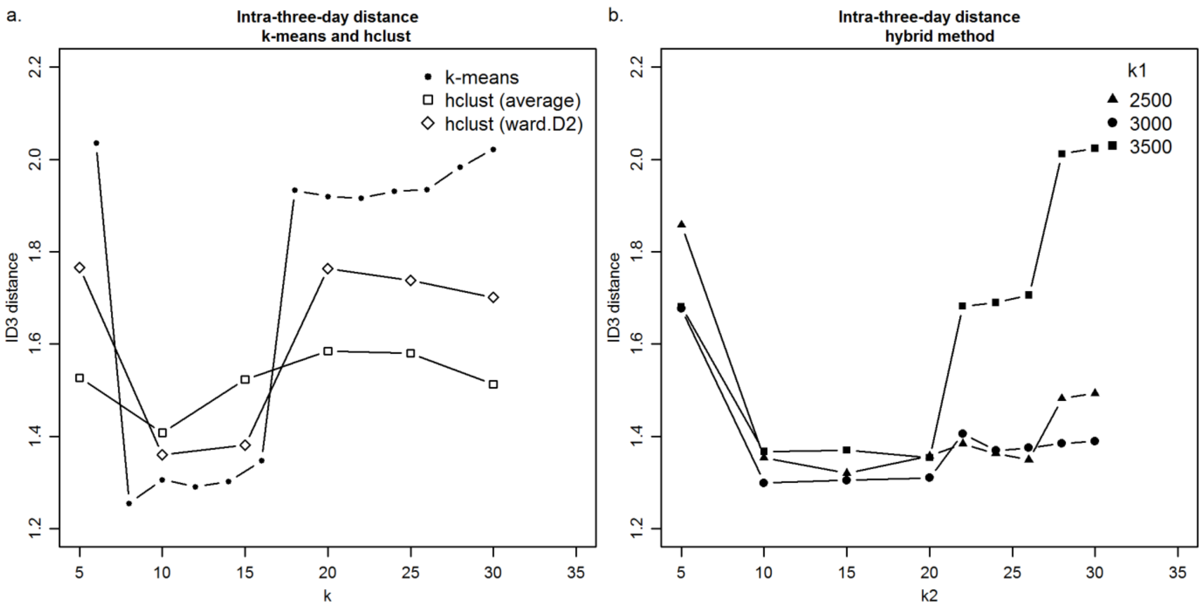

Fig 3. I3DD error curves for different values of k. 3a The I3DD error curves for different values of *k* for *kmeans* and *hclust* clustering of the 12-day dataset. 3b. The I3DD error curves for different values of *k1* and *k2* for the hybrid clustering method on the same 12-day dataset.

Experiment 2: Clustering 26 months of acoustic data

The Dataset

The dataset for experiment 2 was derived from the 13 months of recording from the 22 June 2015 to the 23 July 2016. This resulted in 1,141,147 vectors of acoustic indices, one vector per minute. After removing one of each pair of indices having a Pearson's correlation greater than 0.7, we retained twelve indices per feature vector: Background Noise (BGN); Signal to Noise Ratio (SNR); Activity; Events per second; Low Frequency Cover (LFC); Mid Frequency Cover; High Frequency Cover; Entropy of Peaks Spectrum; Entropy of Average Spectrum; Entropy of spectrum of Coefficient of Variation; Acoustic Complexity (ACI) and Cluster Count. The values for each index were normalised between the 1.5 and 98.5 percentiles.

Methods

To accommodate the increased size and complexity of the 26-month data set (compared to the 12 day data set), the optimum values for $k1$ and $k2$ in Algorithm 4 were recalculated. The range of $k1$ values explored was 15000 to 27500 in steps of 2500. We expect this range of k1 values will capture the complexity of most datasets. $K2$ values were tried from 10 to 100 in steps of five. The optimum combination was $k1$ = 25000 and $k2$ = 60 (Fig 4). The corresponding dendrogram for the 12 acoustic signatures is shown in Fig 5. Note that the dendrogram has two main branches corresponding to the sites of Woondum and Gympie. Only day 12 (4th September) is 'misplaced' in the tree. This may be due to a continuing response to rain events that occurred on the previous day (3rd September 2015).

Cluster interpretation

Five methods were used to determine the acoustic content of the one-minute audio segments in each cluster. The seven major classes of acoustic event found were: Quiet, Wind, Birds, Orthopterans (crickets), Cicadas, Rain and Planes.

The majority of clusters contained events from a dominant source and their assignment to a class was relatively straight forward. Deciding how to group the remaining clusters (helpful because it allowed colour coding for subsequent imaging), was based on the dominant event types as well as multiple sources of evidence as described below.

In addition to listening to a sample of each cluster, we also employed a number of statistical based methods to confirm the consistency of the clusters. The five methods were:

i. Listening to a random sample of 20 one-minute recordings from each cluster.
ii. Mapping of the cluster medoids onto two dimensions using a Sammon projection (*sammon* function in R MASS package (Venables & Ripley, 2002); *pam* function in R cluster package (Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2015)). A Sammon map is used to map high dimensional data to a lower dimension (in our case two dimensions) while attempting to preserve the inter-point distances (Sammon, 1969). This visualises the relationships between the clusters/acoustic states.
iii. Plotting the temporal distribution of clusters: 24-hour histograms of cluster occurrence are likely to reveal cluster content. For example, clusters (acoustic states) dominant around dawn suggests their content is morning bird chorus. Clusters dominant at evening suggests insect chorus or quiet.

iv. Producing composite false-colour spectrograms: These images are prepared by concatenating the one-minute representations (from the corresponding 24-hour false-colour spectrogram) of 600 randomly selected minutes from each cluster.

v. Comparing cluster medoids using radar plots: The values of the 12 acoustic indices (normalised) in each cluster medoid indicate which indices are important in defining the cluster.

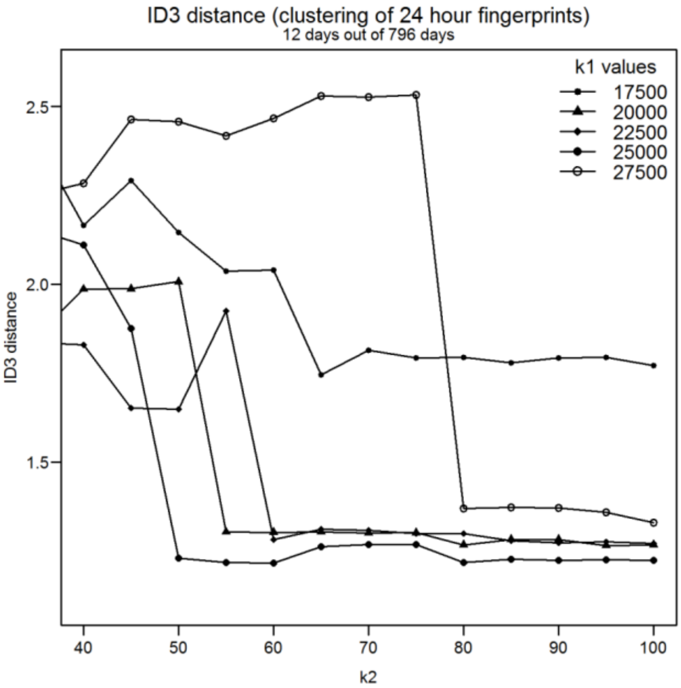

Fig 4. I3DD 'error' versus k1 and k2 for the hybrid clustering method on the 26 month dataset.

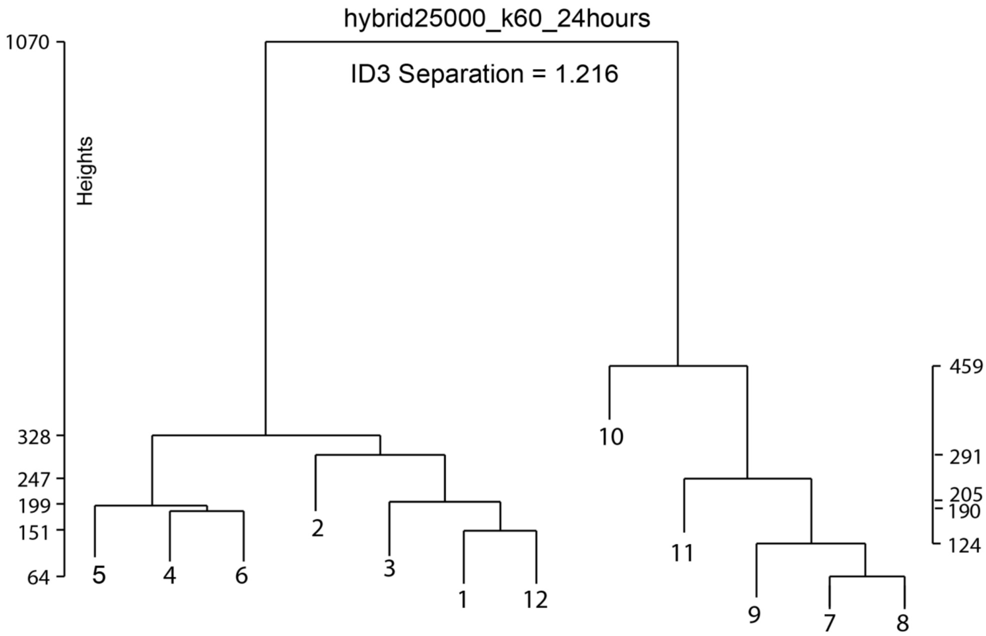

Fig 5. Dendrogram for the optimal (i.e. minimum I3DD error) hybrid run (k1 = 25000, k2 = 60). The left branch of the tree corresponds to recordings from the Gympie Site (except for day 12) and the right branch corresponds to recordings from Woondum. Only leaf 12 is not in its 'correct' branch.

Maps and photos of site

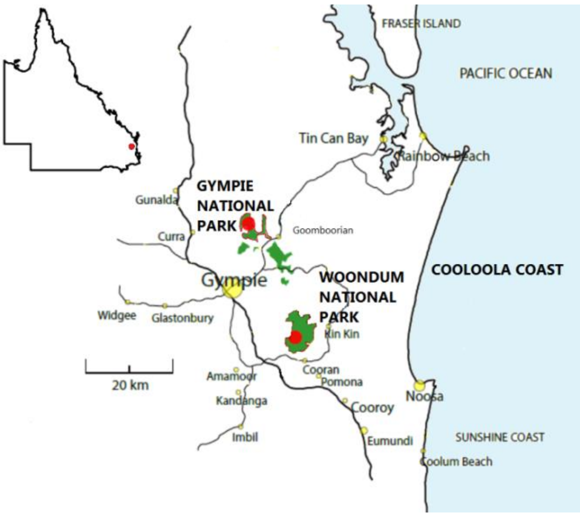

Fig 6: Regional map showing the relative location of the two sites (in red) and the city of Gympie and the Queensland coast (drawn by author YP).

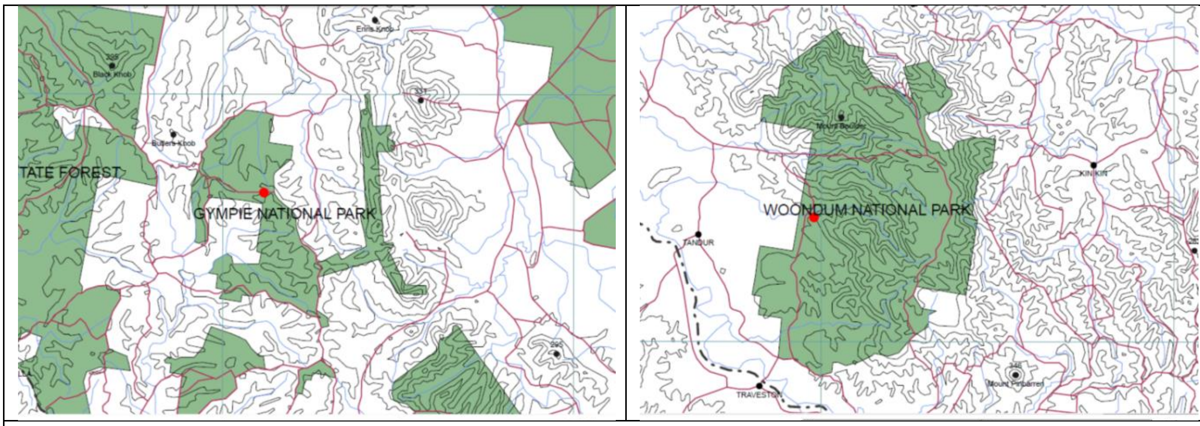

Fig 7: Location of acoustic recorder within Gympie National Park (left) and Woondum National Park (right) (Adapted from shape files available from the Australian Government Geoscience Australia (2006)).

Fig 8: Photographs of the recording sites, Gympie National Park (left) and Woondum National Park (right). (photos taken by author YP).

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