Inteligencia Artificial, 26(71) (2023), 34-45
doi: 10.4114/intartif.vol26iss71pp34-45

INTELIGENCIA ARTIFICIAL

http://journal.iberamia.org/

Identifying Acoustic Features to Distinguish between Highly and Moderately Altered Soundscapes in Colombia *

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Abstract Numerous acoustic features have been proposed as useful measures to characterize natural soundscapes, which can be employed to examine the impact of land transformation on the audible properties of a location. The extensive collection of available features demands an examination to identify the most informative and discriminative ones for a given problem. In this study, we conduct an empirical investigation into the selection of acoustic features for discriminating between highly and moderately transformed versions of four Colombian soundscapes: moorlands, coffee plantations, dry tropical forests, and pastures. We employ classical supervised feature selection techniques along with exploratory tools such as correlation matrices and scatter plots. Our results indicate that a few acoustic features are sufficient to differentiate between the classes. Specifically, those features that estimate acoustic complexity via intrinsic variability of sound intensities or biodiversity through species richness or abundance in specific frequency bands are the most discriminative ones. These findings suggest that the selection of acoustic features can assist in analyzing and distinguishing between different soundscapes.

Keywords: Acoustic features, Classification, Feature selection methods, Soundscapes.

1 Introduction

Pattern recognition (PR) and Machine Learning (ML) are considered a branch of Artificial Intelligence (AI) [1]. Indeed, AI covers, according to [20, p. 135], the fields of expert systems, fuzzy logic, artificial neural networks/deep learning, natural language processing, machine vision, robotics and ML. The latter refers to the ability of predicting either class labels or future values from examples, which are represented as points in some vector space. In such a space, each dimension is called, in the PR/ML terminology, a feature. Therefore, the space itself is often referred as the feature space.

Recently, AI applications related to ecological and environmental concerns have been categorized within the denomination of *AI for social good* (AI4SG) which, according to [22], is understood in relation to the 17 United Nations Sustainable Development Goals. In particular, one of those applications is the

*A first version of this paper was published in [15], which we experimentally extended by including results with two additional datasets. Discussions and conclusions were also updated accordingly.

ISSN: 1137-3601 (print), 1988-3064 (on-line)

development of efficient and effective sound-based monitoring systems for environmental management and conservation, such that non-invasive and semi-automated AI techniques are used for the conservation of biodiversity, ecosystems and landscapes [7]. This aim has also been called Ecoacoustics, and has become a growing field of study that focuses on the analysis of acoustic data to better understand the environment and the relationship between species, ecosystems, and anthropogenic activities [8].

Acoustic features are an important tool for the analysis and characterization of soundscape data in Ecoacoustics; in particular, they can provide insight into ecological processes and changes occurring in the environment. In Ecoacoustics, authors prefer to use the name *Acoustic indexes* instead of *Acoustic features*; other synonyms include *Acoustic variables* and *Acoustic attributes*. However, in this paper, we use the standard PR/ML terminology; that is, referring to features instead of indexes, variables or attributes.

One of the key components of ecoacoustic monitoring systems —and in general in all PR systems [5]— is the selection of appropriate features. This stage is crucial for the classification and discrimination of different types of soundscape data. The proper selection of these features can lead to better classification accuracy, while an inappropriate selection can lead to reduced accuracy or erroneous results [4]. Therefore, the selection of suitable acoustic features is crucial in Ecoacoustics and has important implications for environmental management and conservation efforts. By choosing informative and discriminative indicators, ecoacoustic monitoring systems can assist in identifying and mitigating anthropogenic impacts on the environment, monitoring changes in ecological processes, and contributing to a better understanding of the complex relationships between species, ecosystems, and human activities.

The importance of Ecoacoustics for the study of Colombian ecosystems was recently discussed in [19]. There, the authors presented examples of highly and moderately transformed soundscapes in Colombia to differentiate between different categories of conservation in each ecosystem. These categories include pure coffee plantations vs. mixed coffee plantations with forest patches, low and high transformed moorlands, and tropical dry forests with low or severe transformations. Even though the examples were presented in that reference with both spectrograms and audio files, there has been no —to the best of our knowledge and apart of our previous study [15]— quantitative analyses of the properties of these soundscapes or selection of the most discriminative acoustic features for distinguishing between the different categories of conservation. In a similar effort, the authors of [16] discuss a study conducted in the piedmont plain of Meta (Colombia), where the soundscapes of four cattle farms were recorded. The data correspond to traditional livestock farming systems and silvopastoral wooded pastures. The joint consideration of soundscapes from those four habitats (namely, moorlands, coffee plantations, tropical dry forests and pastures) allows to obtain a good representation of some of the main Colombian ecosystems [10]; indeed, a recent annual biodiversity report from Colombia remarks on the importance of the first three ecosystems by dedicating the following individual chapters to them: [18, 9], [14] and [17, 13], respectively. Moreover, tropical dry forests are particularly endangered due to their generalized transformation to extensive cattle pastures.

Therefore, in this paper, we examine classical techniques of supervised feature selection [12, Chap. 7] for the characterization of data from the four above-mentioned Colombian soundscapes, in order to assess their ability to discriminate between two conservation categories (highly and moderately transformed) in each case and using acoustic features originally proposed in the ecoacoustic literature. We employ various supervised feature selection methods to identify the best individual features and the best feature subsets. The rest of this paper is organized as follows: Sect. 2 provides a brief overview of acoustic features and supervised feature selection methods. Sect. 3 presents and discusses the results of applying these methods to the four above-mentioned examples of Colombian soundscapes. Finally, in Sect. 4, we offer concluding remarks and suggest directions for future work.

2 Background and Methods

2.1 Acoustic features

Eldridge and Guyot [6] recently outlined the main acoustic features proposed in the literature and provided an associated Python library with their implementations, categorizing them into ecoacoustic features, spectral features, and temporal features. Ecoacoustic features are particularly designed for characterizing soundscapes and studying complexity from an ecological point-of-view, while spectral features are directly computed from the spectrogram and can be used to characterize any audio signal. Temporal features, on the other hand, are directly computed from the signal waveforms.

In this work, we consider the acoustic features surveyed by Eldridge and Guyot, as well as the Ecoacoustic Global Complexity Index (EGCI) recently proposed by Colonna et al. [3]. For the latter, we also use a Python implementation which is available in [2]. Table 1 provides a list of all the acoustic features that were considered in our study. As several features correspond to summary statistics of the same attributes, many of them may be potentially redundant. Therefore, applying feature selection methods is required in order to avoid such redundancy and reduce the dimensionality of the feature space.

Table 1: Acoustic features considered in this study.

ID number	Feature names
1 to 7	Acoustic Complexity Index (main, min, max, mean, median, std, var)
8, 37	Acoustic Diversity Index (main, NR main)
9, 38	Acoustic Evenness Index (main, NR)
10, 39	Bioacoustic Index (main, NR)
11	Normalized Difference Sound Index - NDSI
12 to 17	RMS energy (min, max, mean, median, std, var)
18 to 23	Spectral centroid (min, max, mean, median, std, var)
24, 40	Spectral Entropy (main, NR)
25	Temporal Entropy
26 to 31	Zero Crossing Rate - ZCR (min, max, mean, median, std, var)
32 to 35	Wave Signal to Noise Ratio (SNR, Acoustic activity, Acoustic events, Average duration)
36	Number of Peaks
41	Normalized Entropy
42	Ecoacoustic Global Complexity Index

2.2 Feature selection methods

Contrary to what one might think, increasing the number of explanatory variables does not generally improve the predictive ability of a model. As the dimensionality of the data representation space increases, the volume of this space grows exponentially, causing the data to become sparse. To obtain a statistically reliable result, the amount of data needed must increase exponentially with dimensionality. This is known as the curse of dimensionality [11, Sec. 3].

Discovering the best subset of features is a problem of combinatorial search, which means that it can be very computationally expensive. However, there are some suboptimal feature selection methods available for the supervised case, which vary in the applied criteria for evaluation and the selected search algorithms. The most favored evaluation criteria are those that are based on the ratio of inter-intra class distances and the performance of a classifier that does not require parameters, like the nearest neighbor (NN) rule.

The selection methods that were taken into account for this study are the primary ones whose implementations are available in PRTools[1]. A brief summary of these methods is given below, although additional information can be found in [12, Chap. 7].

- *Individual selection* ranks features according to their independent ability to separate the classes.

- *Forward selection and backward selection* search for a subset of features by either adding features (forward search) or sequentially removing them (backward search). Backward selection requires more computations than forward selection [11, Table 5]; thereby, the forward selection is typically preferred.

[1] `http://37steps.com/prtools`

- *Float selection* is a refined version of forward selection, known as its floating variant, and provides the best tradeoff between a nearly optimal result and an affordable computational cost to perform the search.
- *Branch-and-bound* is a recursive but computationally tractable method that guarantees that the optimal subset is found, provided that the evaluation criterion (i.e. the objective function of the optimization procedure) is monotonous. However, satisfying this monotonicity requirement is difficult, as classification performance while including/excluding features is far from being monotonously increasing or decreasing. The implementation also requires the specification of a desired cardinality of the feature subset.

3 Results and Discussion

In the experiments we considered four datasets, each one consisting in a binary classification problem as follows:

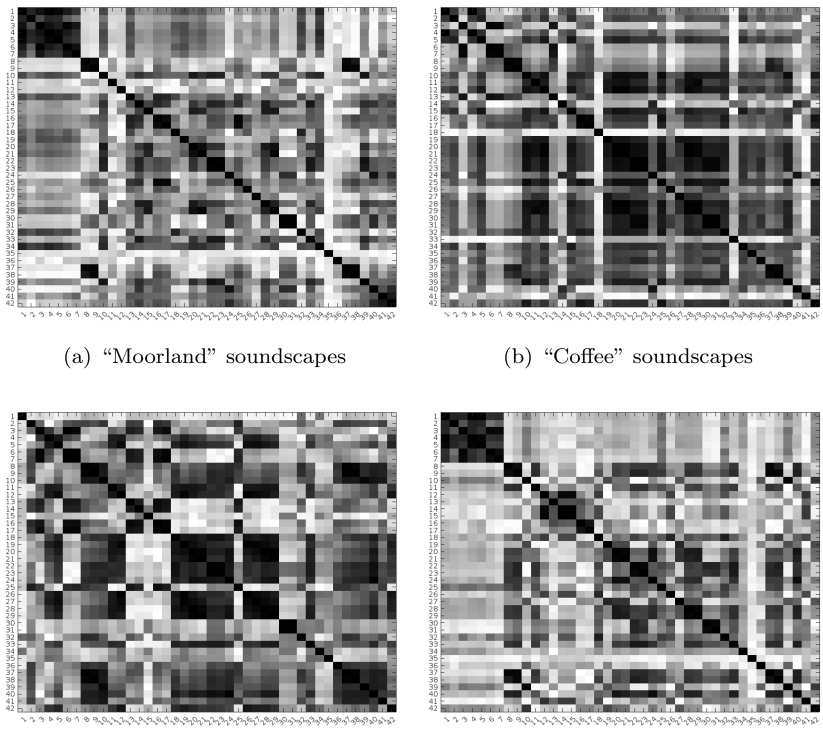
- Moorland:
  - *High transformation moorland*: one audio of 10 minutes
  - *Low transformation moorland*: one audio of 10 minutes
- Coffee:
  - *Monoculture coffee plantations*: one audio of 10 minutes
  - *Mixed coffee plantations with forest patches*: one audio of 10 minutes
- Forest:
  - *Dry Tropical Forest with high landscape transformation*: one audio of 5 minutes
  - *Dry Tropical Forest with low landscape transformation*: one audio of 5 minutes
- Pastures:
  - *Wooded pasture*: 94 audios of 1 minute
  - *Traditional pasture*: 85 audios of 1 minute

The first three problems are provided by the Humboldt Institute[2]; for the Moorland problem the audios were recorded at Chingaza Natural Park and those of the coffee plantations were acquired in locations near Belén de Umbría. All recordings were sampled at 48 kHz and cleaned using a 1 kHz high-pass filter to remove wind noise perturbations [19]. These 10 minute audios were segmented into 1 minute windows with a 50% overlap (i.e., 30 seconds), and the feature indices shown in Table 1 were calculated for these audios. This resulted in a composite dataset for the Moorland and Coffee problems, each one with 19 points in the feature space, and therefore the data matrices corresponding to these problems have 38 observations (rows) and 42 features (columns).

Regarding the Forest problem, the process was similar, taking into account that each audio was half the duration of the Moorland and Coffee problems. This resulted in a data matrix of 20 observations (rows) and 42 features (columns). Regarding the Pastures problem, these data are associated with the study in [16] and are available to be downloaded from the ARBIMON platform[3]. In this work, we considered a subset of this dataset, specifically those corresponding to La Pradera, a livestock farm in the piedmont of the Colombian Orinoco in the department of Meta. The recordings were made on November 24 and November 29, during the time intervals of 06:00-07:00, 12:00-13:00, 18:00-19:00, and 00:00-01:00, with a duration of one minute taken at 10-minute intervals, in two types of pastures: wooded pastures and traditional pastures. According to that, we extracted 94 files corresponding to wooded pastures and 85 to traditional pastures. We calculated the same features for each of these files as for all of the other datasets, and formed the data matrix, which has 179 observations (rows) by 42 features (columns). We had to discard seven audio files that presented problems when calculating some of the features.

[2]The audio files are available at: `http://colecciones.humboldt.org.co/rec/sonidos/publicaciones/ret2019/`
[3]Audio files available in `https://arbimon.rfcx.org/project/sustainable-cattle-ranching-in-colombia/dashboard`

The first step of the analysis involved calculating the correlation matrices for the two classification problems. The matrices were then displayed in Fig. 1 using absolute values of the correlation coefficients. This was done to focus on the strength of the relationships between acoustic features rather than on their direction. Darker entries in the matrices indicate stronger relationships between pairs of features. Certain groups of acoustic features were found to be highly correlated, such as the top-left corners of (Fig. 1(a) and Fig. 1(d)), which corresponds to summary statistics of the Acoustic Complexity Index.



(a) “Moorland” soundscapes

(b) “Coffee” soundscapes

(c) “Forest” soundscapes

(d) “Pastures” soundscapes

Figure 1: Correlation matrices for the four studied classification problems.

Taking into account the information observed in the correlation matrices, we proceeded to apply the selection methods described above, which we will call: Individual Selection, Forward Selection, Float Selection and Branch-and-Bound.

If the desired size of the feature subset is not specified, we use Float Selection to find the best subset, as this method presents a good balance between the quality of the result and computational cost. Considering that we have few observations in most of the considered datasets, we also restrict ourselves to apply the leave-one-out NN classification performance as evaluation criterion for all the methods; indeed, according to [11], the NN performance is a common exemplar feature selection criterion. Furthermore, some other methods such as those based on either the inter-intra distances or the sum of Mahalanobis distances tend to be ill-posed for small-sample problems due to the inversion of almost singular matrices.

3.1 Individual Feature Selection

The individual selection method produces a list of the features ranked in order of their significance for distinguishing between the classes. The feature rankings for the four soundscape classification tasks are provided below, where the features are referred to by their ID numbers as specified in Table 1 in order to save space.

- *Moorland:* The ranking of the features for this problem is the following one: 5, 1, 4, 35, 18, 3, 2, 11, 40, 34, 13, 19, 24, 6, 7, 26, 27, 32, 38, 8, 37, 9, 12, 20, 30, 31, 42, 14, 16, 17, 25, 41, 10, 15, 21, 29, 33, 39, 22, 23, 36 and 28. It is worth noting that the most effective feature in distinguishing between the two classes of the Moorland soundscape is the median of the Acoustic Complexity Index. The next two most effective features are also related to the same acoustic attribute, specifically the main value and the mean. Hence, in summary, the Acoustic Complexity Index is the most informative feature for discriminating in this particular problem.

- *Coffee*: The ranking of the features for this problem is the following one: 10, 11, 12, 15, 19, 20, 21, 28, 29, 18, 25, 5, 22, 23, 27, 30, 31, 32, 13, 16, 17, 34, 35, 36, 39, 42, 2, 24, 9, 26, 1, 4, 14, 3, 38, 8, 37, 6, 7, 33, 40 and 41. The top-ranked feature for discriminating between the two classes of this case is the main value of the Bio Acoustic Index, followed by the Normalized Difference Sound Index and then the minimum of the RMS Energy. Therefore, the most important information to discriminate in this case is provided by these three acoustic features.

- *Forest*: The ranking of the features for this problem is the following one: 3, 4, 5, 11, 12, 18, 19, 20, 21, 22, 23, 26, 27, 28, 29, 42, 8, 9, 24, 25, 37, 38, 40, 1, 2, 13, 15, 32, 36, 6, 7, 16, 17, 33, 10, 41, 30, 31, 39, 14, 35 and 34. For this problem, the results are similar to those of the Moorland case, with the first three positions occupied by statistics of the Acoustic Complexity Index.

- *Pastures*: The ranking of the features for this problem is the following one: 5, 1, 4, 3, 22, 23, 10, 30, 31, 18, 20, 9, 25, 8, 21, 19, 12, 24, 2, 40, 26, 33, 34, 37, 28, 14, 29, 16, 17, 39, 27, 41, 42, 11, 13, 35, 36, 38, 6, 7, 15 and 32. For this problem, once again, the Acoustic Complexity Index shows the highest discrimination power, just like in the Moorland and Forest cases.

The use of individual selection gives some information but, as previously mentioned, the most important features individually selected do not necessarily form the best subset. Therefore, we must investigate the performance of feature combinations. Specifically, we searched for the best pair, triple, and group of features. We examined the first two cases to easily visualize the corresponding scatter plots, and we considered the last case to avoid any constraints on the resulting dimensionality of the feature vectors.

3.2 Selection of the Best Pair of Acoustic Features

In order to find the best pair of features for our analysis, all the selection methods described in Sect. 2.2 were used, except for backward search. The NN performance was used as our evaluation criterion, and the selected features per method are listed below. Additionally, the scatter plots for each selected pair of features are reported in Fig. 2.

Moorland:

- *Float* and *Forward:* 5 (Median of the Acoustic Complexity Index) and 9 (Main value of the Acoustic Evenness Index).

- *Branch-and-bound:* 35 (Average duration of the Wave SNR) and 5 (Median of the Acoustic Complexity Index).

Coffee:

- *Float*: The method only returns feature 10 (Main value of the Bio Acoustic Index) as the selected one.

- *Forward*: 10 (Main value of the Bio Acoustic Index) and 2 (Minimum of the Acoustic Complexity Index).

- *Branch-and-Bound*: 28 (Mean of the ZCR) and 29 (Median of the ZCR).

Forest:

- *Float*: The method only returns feature 3 (Maximum value of the Acoustic Complexity Index) as the selected one.
- *Forward*: 3 (Maximum value of the Acoustic Complexity Index) and 2 (Minimum of the Acoustic Complexity Index).
- *Branch-and-Bound*: 29 (Median of the ZCR) and 42 (Ecoacoustic Global Complexity Index).

Pastures:

- *Float* and *Forward:* 5 (Median value of the Acoustic Complexity Index) and 39 (Bioacoustic Index NR).
- *Branch-and-Bound*: 4 (Mean of the Acoustic Complexity Index) and 5 (Median of the Acoustic Complexity Index).

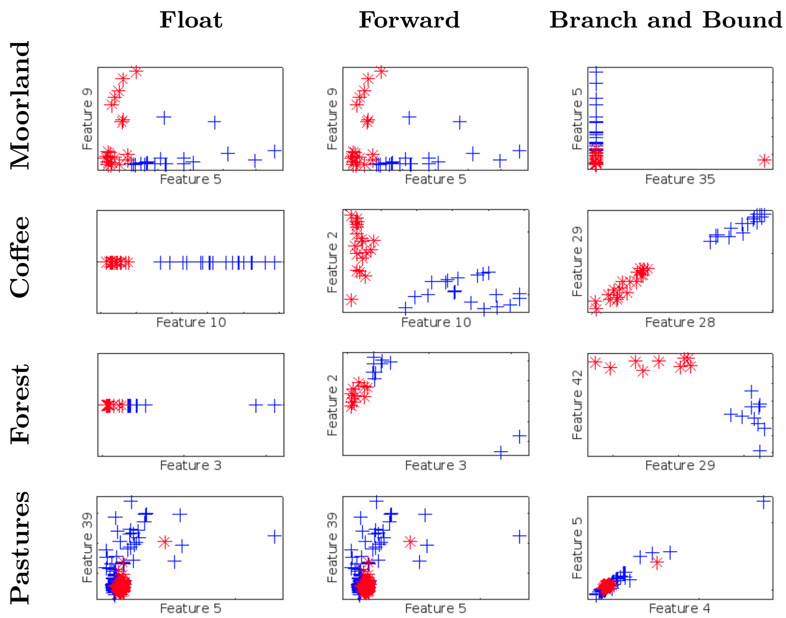


Figure 2: Scatter plots for the best pairs of acoustic features per classification problem and selection method.

3.3 Selection of the Best Triple of Acoustic Features

In a similar way, we applied the same selection methods and evaluation criterion to select a subset of three features. The chosen triples of features per method are presented below, while their corresponding scatter plots can be found in Fig. 3.

Moorland:

- *Float*: This method reports that only two features are needed: 5 (Median of the Acoustic Complexity Index) and 9 (Main value of the Acoustic Evenness Index).
- *Forward*: 5 (Median of the Acoustic Complexity Index), 9 (Main value of the Acoustic Evenness Index) and 8 (Main value of the Acoustic Diversity Index).
- *Branch-and-bound*: 4 (Mean of the Acoustic Complexity Index), 35 (Average duration of the Wave SNR) and 5 (Median of the Acoustic Complexity Index).

Coffee:

- *Float*: A single feature is required, namely feature 10 (Main value of the Bio Acoustic Index).
- *Forward*: 10 (Main value of the Bio Acoustic Index), 2 (Minimum of the Acoustic Complexity Index) and 4 (Mean of the Acoustic Complexity Index).
- *Branch-and-Bound*: 21 (Median of the Spectral Centroid), 28 (Mean of the ZCR) and 29 (Median of the ZCR).

Forest:

- *Float*: A single feature is required, feature 3 (Maximum of the Acoustic Complexity Index).
- *Forward*: 2 (Minimum of the Acoustic Complexity Index) 3 (Maximum of the Acoustic Complexity Index) and 4 (Mean of the Acoustic Complexity Index).
- *Branch-and-Bound*: 28 (Mean of the ZCR), 29 (Median of the ZCR), and 42 (Ecoacoustic Global Complexity Index).

Pastures:

- *Float*: Only two features are reported, 5 (Median value of the Acoustic Complexity Index) and 39 (Bioacoustic Index NR).
- *Forward*: 5 (Median value of the Acoustic Complexity Index), 39 (Bioacoustic Index NR) and 9 (Main value of the Acoustic Evenness Index).
- *Branch-and-Bound*: 1 (Main value of the Acoustic Complexity Index), 4 (Mean of the Acoustic Complexity Index) and 5 (Median of the Acoustic Complexity Index).

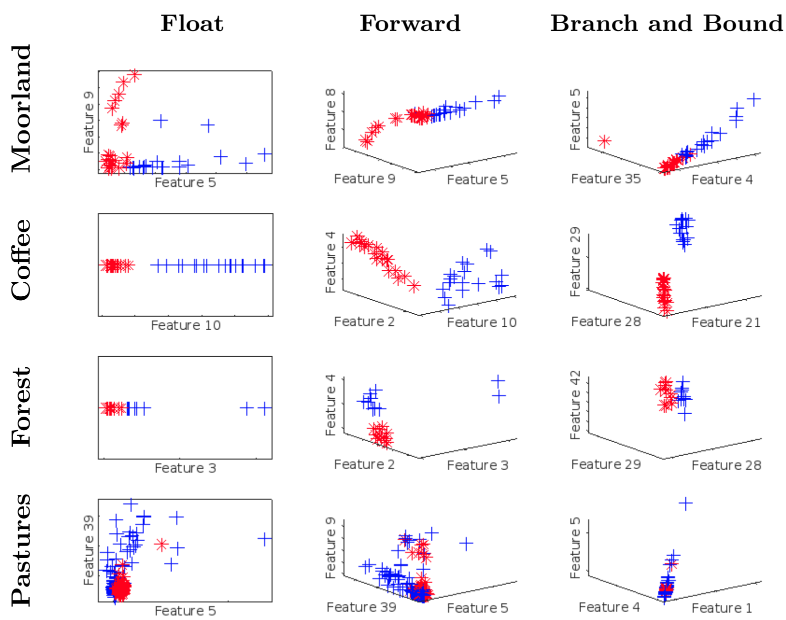


Figure 3: Scatter plots for the best triples of acoustic features per classification problem and selection method.

In the Coffee classification problem, it is interesting to note that the Branch-and-bound method selected two highly correlated summary statistics of the same acoustic feature (ZCR): feature 28 (Mean of the ZCR) and feature 29 (Median of the ZCR), as seen in Fig. 2. A remarkable finding in all classification problems, is that the float and forward selection methods tend to converge in their selection of acoustic features. The float method is a modified version of the forward method, so their results are expected to be similar. However, it is important to mention that the float method consistently selects subsets with smaller dimensionality than specified, selecting only one feature for Moorland, Coffee and Forest when a pair or a triple was desired, or a pair of features for Moorland and Pastures when a subset of three features was sought.

3.4 Selection of the Best Subset of Acoustic Features

To choose the best subset, the float method was used without specifying a size for the subset, so that the best subset is found with the NN criterion. The best subsets for each problem considered are shown below.

Moorland: The best subset is composed by the following three features: 5 (Median of the Acoustic Complexity Index), 11 (Main value of the Normalized Difference Sound Index) and 2 (Minimum of the Acoustic Complexity Index).

Coffee: The best feature subset is a singleton: 10 (Main value of the Bio Acoustic Index).

Forest: The best feature subset is a singleton: 3 (Maximum of the Acoustic Complexity Index).

Pastures: The best feature subset is composed by the following three features: 5 (Median of the Acoustic Complexity Index), 10 (Main value of the Bio Acoustic Index) and 11 (Main value of the Normalized Difference Sound Index).

Since the cardinalities of the best found subsets are lower than three, the corresponding scatter plots can be visualized; see Fig. 4.

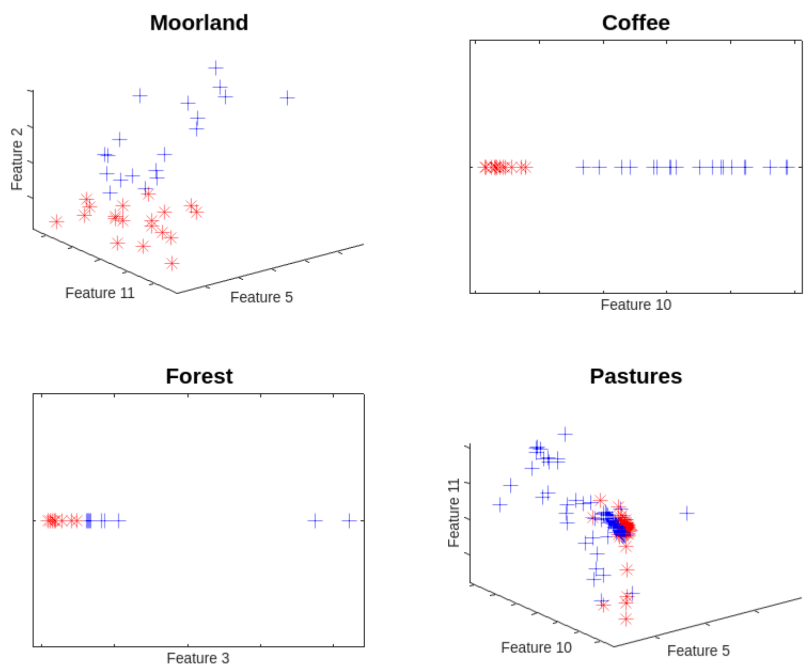


Figure 4: Scatter plots for the best subsets of acoustic features, per classification problem, found by float selection.

It is worth noting that for Moorland, the float method selected a triple subset consisting of two statistics of the Acoustic Complexity Index: its median (feature 5) and minimum (feature 2) values.

However, these two features show a high correlation coefficient, as evidenced by a visual inspection of the top-left corner in Fig. 1(a), suggesting that the method did not find a subset of informative and independent acoustic features. It is important to remember that float selection can only guarantee the optimal solution if a monotonic function is optimized.

4 Conclusion

In this work, a supervised feature selection was conducted to discriminate between two classes of soundscapes (lowly-transformed and highly-transformed), using four datasets from different types of soundscapes found in Colombia (Moorland, Coffee, Forest, Pastures). It is important to note that, in feature selection, the objective function generally depends on a subset of features, and this makes the function non-monotonic. Adding or removing features from a subset does not guarantee that the function always increases or decreases, and many methods require a monotonic function to ensure optimal subset selection [11].

It is noteworthy that for all datasets, the Acoustic Complexity Index (ACI) was considered a discriminant feature. For Moorland, Coffee, and Forest, the majority of the selected features were temporal (ZCR, SNR) using the Branch-and-Bound method, while Float and Forward methods selected mainly ACI statistics and the main values of Acoustic Diversity Index or Bioacoustic Index (BI). For Pastures, all methods selected ACI statistics.

Coffee and Forest were completely separable, with one feature being sufficient. For Coffee, the Bioacoustic index was the best feature; however, it does imply that such a feature is the only one providing a good or even the best separation. For Forest, the maximum of ACI was the best one. For Moorland and Pastures, the best subsets were composed of three features each. In Moorland, the selected features were 5 and 2, which were statistics from the same ACI index, along with NDSI. In Pastures, the selected features were 5 (ACI median), 10 (BI), and 11 (NDSI).

It can be observed that in some soundscapes, clusters are formed within the classes, especially in Forest and Pastures; see Fig. 4. In the case of Pastures, this could be due to the audio recordings being taken at different times over several days, which can form natural groups.

Aside from the binary classification task, it is possible to calculate a measure of the degree of transformation as a means of determining how close a feature point, which represents a particular soundscape, is to the decision boundary. Future research will involve exploring alternative supervised techniques, such as those that utilize evolutionary computation (such as genetic algorithms), as well as unsupervised feature selection methods [21], other supervised feature selection methods [12, Chap. 7] and non-negative matrix factorization algorithms for feature selection.

Acknowledgments

The authors acknowledge support from Universidad Nacional de Colombia - Sede Manizales and Ministerio de Ciencia, Tecnología e Innovación - Minciencias, República de Colombia [Programa de excelencia doctoral del Bicentenario, 2019]. Editors of Inteligencia Artificial are also acknowledged for their kind invitation to prepare this extended journal version of our IBERAMIA 2022 conference paper.

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