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EXPLORING ACOUSTIC DATA WITH INFORMATION VISUALIZATION

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Exploring acoustic data with Information Visualization

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Abstract

Sound is an important tool to understand natural and urban landscape dynamics. Nonetheless, the available amount of audio files recorded to this goal has been increased at a large level. Current efforts in soundscape interpretation such as larger audio sets apply visual techniques to summarize and explore this data, allowing interpretation of ecological characteristics of natural areas, for example. In this report, we present a way to process and visually explore audio sets to support the understanding of natural relationships, helping knowledge acquisition that can be used to decision making related to monitoring and conservation natural areas.

Keywords: ecoacoustics, soundscape, visual analysis, visual exploration

1. Introduction

The technological advance and the low price of the recording equipment enlarged the number of audio recordings, generating several challenges to specialists from the Soundscape area. The quantity of audio reached many terabytes in just a few years [1, 2, 3, 4, 5]. Therefore, there is a great necessity for suitable strategies to improve knowledge acquisition based on soundscape audios. Data visualization techniques are needed tools to improve data analysis in these circumstances, providing ways to explore large datasets to understand and explain ecological content contained on sounds.

Visual tools take advantage of sight, that is a key sense to understand information, to give support to data analysis (Section 2.1). These techniques communicate information through graphic representations generated by the computer, showing visual data alternatives and helping the description of data structure, patterns, and outliers [6]. As a result, these approaches, applied to soundscape analysis, can aid the decision-making in controlling species, environmental monitoring of preservation areas, and in the quality analysis of health and biodiversity of the environment [7, 8, 9].

The main question of this report is related to the visual processes applied to analyze audio datasets and it follows part of the process proposed by Dias [10]. Towards this goal, it is necessary *i)* to process data, and *ii)* to select few techniques to aid visual analyses. The results follow increment research, such as the ones proposed by Phillips et al. [5] and Reis et al. [11].

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This report is organized as follows. Section 2 briefly reviews the relevant concepts used here. Section 3 presents other researches that apply visual techniques to dial with soundscape analyses. Section 4 describes the proposed process and materials utilized to develop it. Section 5 reports some experimental results. Section 6 presents a brief discussion of the results. Section 7 concludes the report with some final remarks and directions for other works.

2. Basic concepts

Currently, several areas provide tools to analyze and explore data, such as statistics, machine learning, data visualization, etc. These tools can be (semi) automatic or dependent on some user interaction. The interaction with humans provides the insertion of knowledge that are scarce or difficult to map inside an automatic process. Beyond that, just numerical approaches can lead to a misinterpretation. In a specific scenario, datasets can have the same statistics (mean, variance, deviation, etc), but distinct visual patterns [12]. This way, visual approaches are capable to bridge the gap between analysis and a correct data interpretation. Next sections present visual tools and steps to process data and apply visualizations to explore it.

2.1. Data visualization techniques

Intending to extract knowledge about large and complex datasets, Information Visualization (InfoVis) techniques apply visual representations to aid users to understand attributes and relationships amid data. These techniques focus on data with no intrinsic physical attributes that have an abstract representation, such as knowledge inside a group of texts, the influence of a user in a social network, patterns into a relational database of the stock market, etc [13, 14].

Depending on needs, data can be processed before any visual exploration. In some cases, data needs to be converted to a numeric representation such as acoustic indices extracted from audio files. In other ones, a dataset is large and some sampling approach is executed to generate small but representative data samples, that facilitate data manipulation. Moreover, the feature set can be compounded by several features such as in text processing. Approaches as manual or automatic feature selection and dimensionality reduction can be applied to reduce data dimensionality. In other scenarios, features values have to be converted to another range, transforming values into a manageable representation. It is possible to apply approaches, such as *min-max* normalization[1], standard *z-score*[2], etc [6]. Beyond that, there are data with missing feature values, data with some noise level, and so on. Users can apply several techniques to mitigate these problems, that are available on literature for InfoVis, Machine learning, Data mining, etc.

After the pre-processing step, one needs to specify which visualizations will be used. There are several of them, with distinct characteristics and applications[3]. The next sections describe some of them, applied here to communicate audio feature behavior and relationships.

[1] *Min-max* puts values into $[0, 1]$ range.

[2] *Z-score* forces data to have mean $\bar{x} = 0$ and standard deviation $\sigma = 1$.

[3] The web site `https://www.data-to-viz.com/` has tips to help to choose visualization tools depending on the type of data to be viewed.

2.1.1. Boxplot

Boxplot visually represents the variation of a numeric feature based on statistical measurements known as quartiles, where a range of values is divided into four equal parts. In Figure 1, it is possible to identify *Q1*, *Median* and *Q3*, that respectively represent 25%, 50%, and 75% of the amount of values. Besides, *interquartile range* (IQR) is applied to calculate the minimum and maximum limits used to identify the range and the outlier values. Moreover, the box length and position are related to the skewness of value distribution.

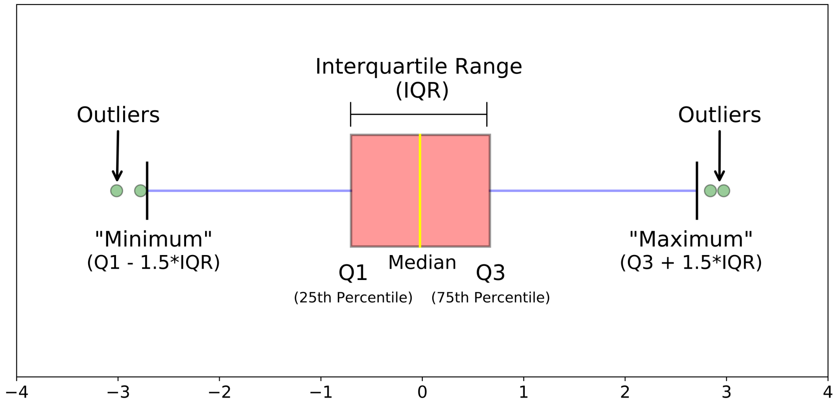

Figure 1: Description of a boxplot chart[15].

2.1.2. Parallel Coordinates

Parallel coordinates are a graph that has parallel instead of orthogonal axes evenly spaced such as Figure 2. These axes represent each coordinate (attribute, feature, dimension, and so on) of data. A data instance is represented as a curve that crosses an axis in the position that represents a value of the instance [14, 6].

Relationships between dimensions and curves that have similar behavior can be perceived. Curves with the same behavior can be interpreted as groups of similar items. The user is able to move axes to aid the analyses. Even though the screen available area limits the amount of the attributes that could be used and the line representation can cause visual confusion.

Figure 2: Simple parallel coordinates that represent a dataset with five features[16].

2.1.3. Heatmap

Heatmaps are often used to present values as colors. Thus, the values of a table cells, for example, are mapped to normalized color space and they are presented in a colored region such as the Figure 3. This visualization helps to verify value variations and trends.

Several color maps can be used and users can expand and compress the color intervals to emphasize or attenuate some value range [6]. This type of color representation is limited to human perception and this can impair visualization of extensive ranges or large values.

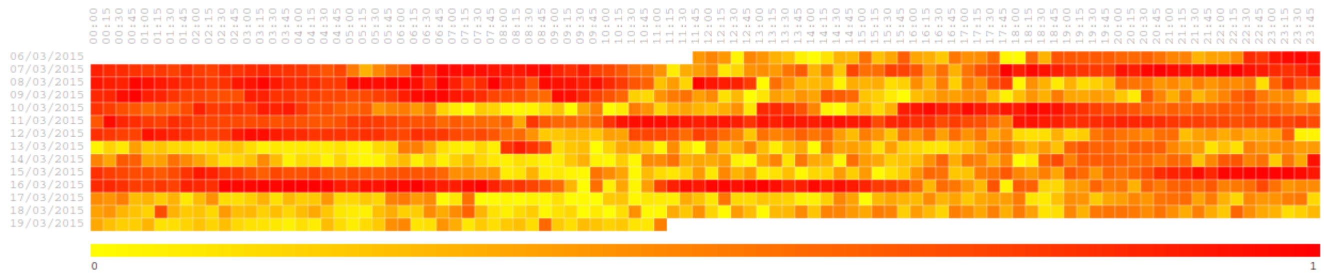

Figure 3: Example of heatmap with values distributed during days (rows) and hours (columns)[10].

2.1.4. Multidimensional projections

Multidimensional projections (MDP) are dimensionality reduction techniques that convert a high-dimensional space of features to a lower one, by the application of mathematical transformations. Frequently, a high-dimensional space has tens, hundreds, or thousands of features and MDP projects them into 2 or 3 dimensions, to create a visual representation such as scatter plots.

MDP techniques have to preserve data properties, such as clustering and segregation relationships among the data. Nonetheless, projections not always attain this goal, owing to the size and dimensions of the data [6], but they have the ability to help visual data exploration, revealing data structures.

To place points in visual space, and preserving relevant properties from the original one, several projection approaches were proposed, such as t-Stochastic Neighbor Embedding (t-SNE) [17], *eXtended Hierarchical Point Placement Strategy* (xHiPP) [18] and so forth.

3. Related work

During the last decade, several researchers have focused their efforts to develop tools to analyze and understand audio patterns with the help of visual approaches. For instance, Towsey et al. [2] built a visualization based on false-color spectrogram. The proposed approach is capable to summarize great amounts of audios, presenting time-dependent ecological patterns. Beyond that, Sankupellay et al. [3] developed a tool that combines the same idea with machine learning techniques to compare distinct landscapes.

Sánchez-Gendriz and Padovese [19] created a visual approach that associates values of an acoustic measure and an event detection technique to represent daily periodical patterns, in a heatmap chart. With the generated view, it is possible to compact large audio sets and accompany sound evolution.

Phillips et al. [5] proposed a sequence of steps to summarize and explore audio sets. They clustered audios and employed visualization techniques, such as histograms, diel plots, MDP, etc., that describe ecological patterns, helping the explanation of environment dynamics.

Ultimately, Reis et al. [11] used correlation matrix (in a heatmap chart) and RadViz [20] to represent acoustic feature relations and their capacity to discriminate distinct acoustic events. The approach can lead the user to select better features to segregate acoustic events, that can improve automatic sound detectors.

4. Material and method

This section presents steps to visually explore and analyze soundscape based on acoustic features. The first one consists of feature extraction. The second step analyses how features behavior with the help of boxplot, parallel coordinates, and heatmaps, and the possible similarities among audios with xHiPP.

4.1. Data used

In tests, we used 4,340 audio files, separated into two groups [10]:

1. **Terrestrial:** data provided by professor Bryan C. Pijanowski from Purdue University, Indiana, USA. These data were collected in two areas in *La Selva* Biological Station, Costa Rica. The first one (CostaRica1) is an old-growth forest near to *Sarapiquí* river. The second one (CostaRica2) is a secondary forest far from the same river but in the same biological station[4]. It was recorded 4 files for each day hour. One file with 10 minutes and others with one minute each one. There are 3,061 files divided in 1,246 from CostaRica1 and 1,815 from CostaRica2. The recording period from CostaRica1 was March 6th to 19th, 2015. The period from CostaRica2 was March 6th to 20th, and April 15th to 20th, 2015. All audio files have Free Lossless Audio Codec (FLAC) format. These audios have sounds of insects, amphibians, rain, engines, etc.;
2. **Underwater:** data provided by professor Linilson R. Padovese from Polytechnic School of the University of São Paulo, Brazil.
   - data collected in *Ilhéus*, south coast of Bahia State, Brazil. It was recorded 480 files with 15 minutes, each one. The recording period was September 3rd to 4th, and September 18th to 22nd, 2014. The dataset was firstly divided into two parts, the first one has 200 audio files (Ilheus1) and the other one (Ilheus2) has 280 files. All audio files have WAVEform audio format (WAV). The humpback whales and fish chorus sounds are predominant in these files;
   - data collected in *Laje de Santos* Marine State Park, the coast of São Paulo State, Brazil. It was recorded 799 files with 15 minutes each one. The recording period was March 17th to 18th, and March 27th to April 3rd, 2015. All audio files have WAVEform audio format. This dataset has sounds of fish, crustaceans, and vessels.

[4]GPS coordinates from the sensor in the old-growth forest: 10.43167528 -84.02136972. GPS sensor in secondary forest: 10.42254278 -84.01599944

4.2. Acoustic indices and measurements

Acoustic indices are employed to soundscape analyses to represent some diversity characteristic. In this report, as proposed by Dias [10], we employed Bioacoustic Index (BIO) [7], Temporal Entropy (H_t), Fequency Entropy (H_f), Acoustic Entropy Index (H) [21], Acoustic Complexity Index (ACI) [8], Acoustic Evenness Index (AEI) [22], M index, Acoustic Richness (AR) [23], Normalized Difference Soundscape Index (NDSI) [24] and Acoustic Diversity Index (ADI) [25].

In addition, other signal measurements were used to evaluate the audio signal, such as Sound Pressure Level (SPL) [26], Number of Peaks (NP), Root Mean Square (RMS) and functions that describe signal variation as Roughness [27] and Rugosity [28].

Finally, Mel-frequency Cepstrum Coefficients (MFCC) [29, 30] were also extracted to help audio description.

4.3. Analysis and exploration

Based on features extracted, statistical and visual analysis can provide invaluable guidance to comprehend and explain audio sets. First and foremost, one can apply descriptive statistics to summarize and describe audio features, comparing them inside a soundscape or to examine differences among soundscapes. Measurements, such as mean, variance, median, minimum and maximum values, entropy, skewness, kurtosis, and so on, are vastly employed to this task. Explanations of these measurements can be encountered in all basic statistical literature and applications of them can be faced in a vast range of papers of soundscape analysis.

Sadly, as aforesaid in Section 2, two or more datasets can have the same statistics but distinct behavior. However, visual tools can aid to explore these datasets and reveal their distinct patterns and we employed a small group of them. *Boxplots* can visually describe statistics, allowing one to figure out the range of values and their dispersion, possible outliers, etc. Associated with it, *parallel coordinates* are useful to grip on patterns and trends of features, their correlations, and so forth.

Heatmaps help to understand how each feature behaves. Different from parallel coordinates, that evaluate several features, this approach can be applied to visualize each feature separately. For example, with heatmaps, it is possible to describe how feature values behave over time and how sensitive a feature is to daily patterns.

Moreover, an audio set can be visualized with MDP technique such as *xHiPP* to understand data relationships of similarity, allowing analysis of sound patterns beyond feature values, and allowing a global visualization of the audio set. With this tool, it is possible to explore significant partitions of the data and highlight important patterns.

Each of these techniques can present distinct views of the data and can enhance the capabilities of each other to describe audio attributes. This provides a broad view of soundscape scenario, helping its description and explanation.

4.4. Material

To extract acoustic features, R packages Seewave[5], Soundecology[6], and tuneR[7] were used in the tests. To generate visualizations, D3.js[8] and xHiPP code[9] were employed.

The parameters used to extract features were the default values of the packages. All FLAC audio files were converted to WAV format, since the packages work with this format to extract features. The values extracted considered all sound time contained in each audio file. The MFCC result is a matrix with coefficients (columns) and their components (rows). Because of that, it was used the column mean to represent MFCC coefficients, and 12 of them were considered in the tests.

5. Visual results

Several analyses of the datasets aforementioned were performed with the application of the tools highlighted in Section 4.3. In the following sections, we show some examples of these explorations that identified patterns in visual displays of soundscapes.

5.1. Boxplot

A boxplot chart is presented in Figure 4 with four measurements (ADI, BIO, H, and SPL) of Costa Rica areas. We normalized the range of values to better represent them on the view.

At first glance, one can verify differences among measurements of the same area, related to their distributions around the median value and represented by the size of the related boxes. Comparisons of distinct places show differences such as the ones of H index. The position of their medians, the greater distance between median and mean of the CostaRica1, distinct spreading of values around the median, and so on. Moreover, the higher median of H from CostaRica2 can point out more audio frequencies or audio amplitudes occupied in that region, which can be occurred by a great number of bird calls, for example.

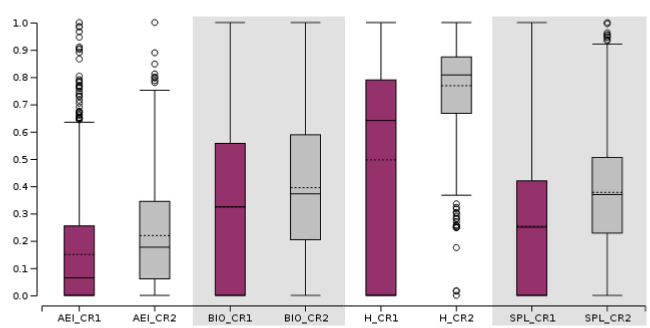

Figure 4: Boxplot chart to compare acoustic measurements of CostaRica1 (CR1) e CostaRica2 (CR2). Range values were normalized to $[0, 1]$ range. Beyond the normal values presented on the boxplot, the average value is represented as a horizontal dotted line inside each box.

[5] http://rug.mnhn.fr/seewave/
[6] http://ljvillanueva.github.io/soundecology/
[7] https://cran.r-project.org/web/packages/tuneR/index.html
[8] https://d3js.org/
[9] https://github.com/fabiofelix/xHiPP

5.2. Parallel coordinate

Figure 5 presents parallel coordinates to analyze values and relationships among acoustic features. Some issues can be pointed out, such as the lowest ACI value is linked with an audio file with recording failures. The largest AEI value is associated with audio that contains specific bird patterns, highlighted on the spectrogram with blue boxes. Another observation is the comparison amid diversity indices. ADI, H, ACI, BIO, and AR have distinct behavior in this scenario, although they are supposed to measure environment properties similarly. Finally, with this visualization, it was hard to verify distinct data trends related to each landscape. Just differences around entropy indices or around rightmost axes, when yellow lines are visible. Thus, probably CostaRica1 and CostaRica2 had similar audio patterns during the collecting period.

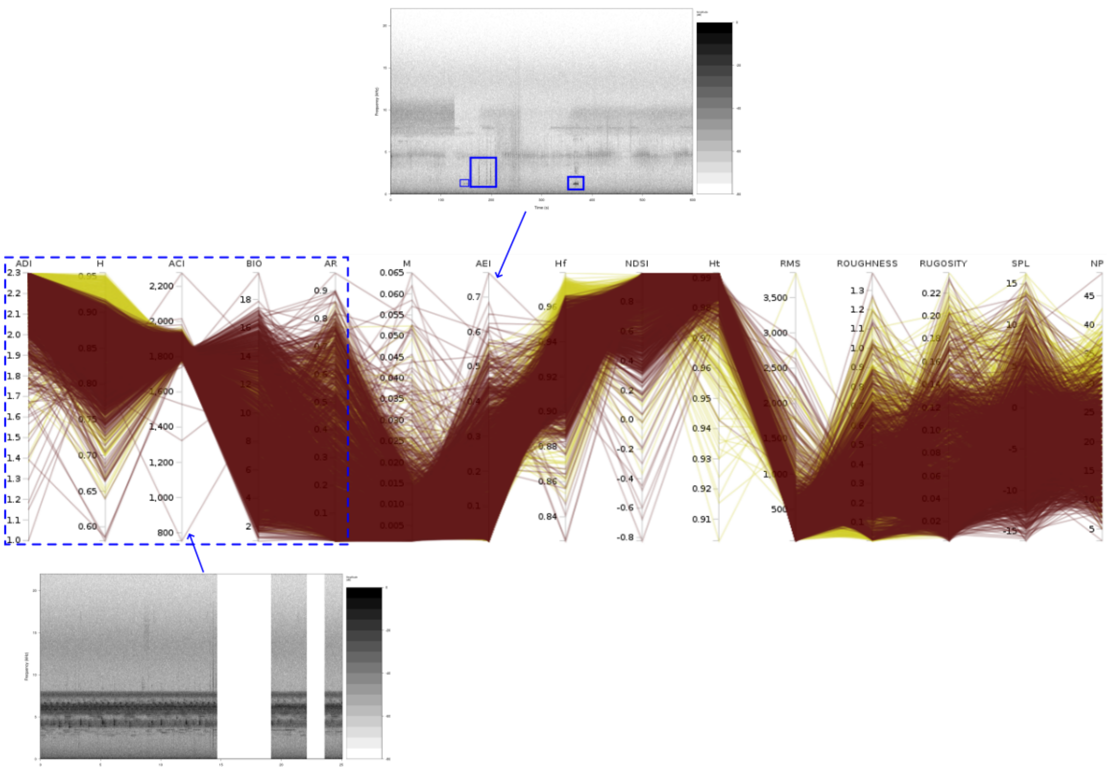

Figure 5: Parallel coordinates of Costa Rica acoustic indices and measurements. Line colors represent CostaRica1 and CostaRica2 areas. The dashed blue rectangle highlight diversity indices. In the AEI axis, the highest value is linked with audio with bird patterns marked with blue on the spectrogram. In the ACI axis, audio with low value is marked and the related spectrogram has recording failures [10].

5.3. Heatmap

Heatmap chart is showed in Figure 6 to evaluate SPL values from CostaRica1 area. This area was employed because it has more samples than others and we randomly chose SPL as an example. SPL presented sensitivity to night audios, such as is delimited by the blue dashed rectangle on the figure right. As shown by the spectrograms displayed in the picture, SPL high values occur both because of rain and because continuous animals sound intensity, and low index values can appear when richer sounds exist.

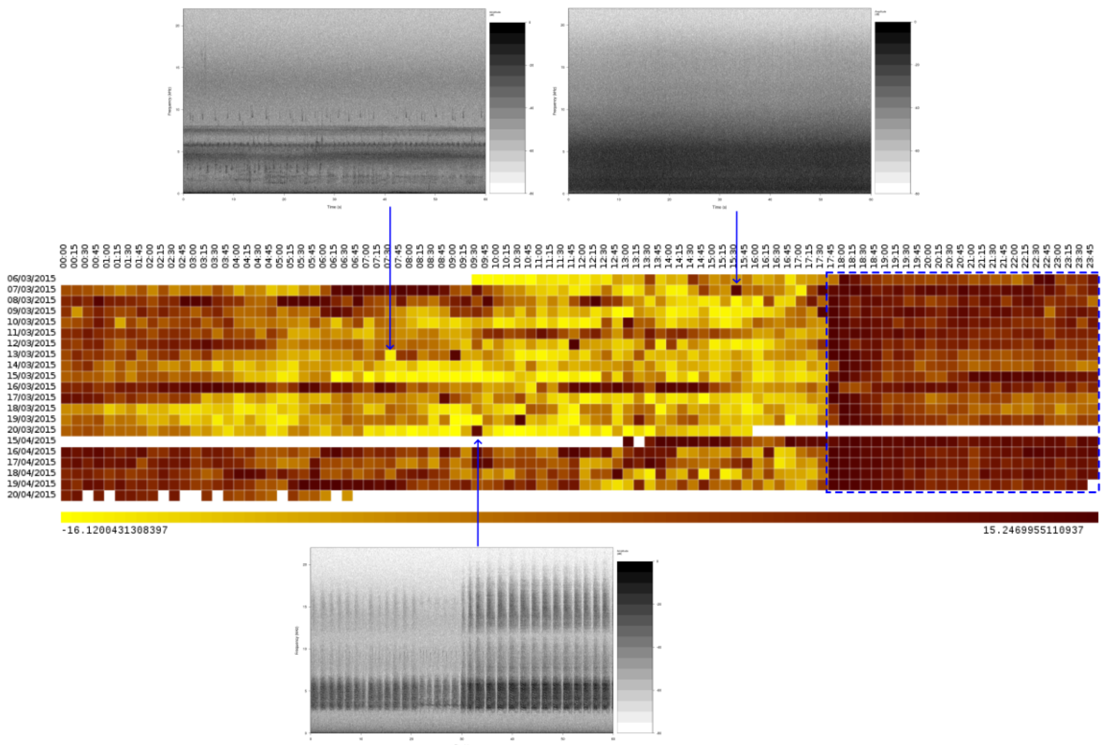

Figure 6: SPL heatmap from the CostaRica1 area. Blue dashed rectangle highlights night values. The top spectrograms indicate, from left to right, SPL low value for audio with animal sound, and SPL high value for audio with rain sound. The bottom spectrogram indicates high SPL value for audio with a high occurrence of cicada sounds [10].

5.4. xHiPP

In this section, xHiPP was applied to assess relationships among audio files and to explore different levels of data clustering. Figure 7 presents *Costa Rica* described by MFCC. Even with good segregation of CostaRica1 and CostaRica2, some points remain mixed. Spectrograms presented on bottom-left point samples from a group whose content is related to rain sounds. Certainly, another pattern occurs (light-blue dotted box), but rain is the predominant event. Spectrograms showed on right are related to a group of audios from the daily period, with insect and bird patterns (light-blue dotted box). On the top, spectrograms present night audios with insect patterns.

The previous data were used in Figure 8, but with colors representing daily period (daytime and nighttime). On the bottom, a spectrogram presents patterns from the night (07:30 pm), such as insects or amphibians that can appear during the period. On the left side, another spectrogram highlights cicada patterns that arose in the daytime (02 pm). Spectrograms of the top and right point bird sound with a constant pattern (maybe insects sound around 10 *kHz*) that emerged during the daytime (05:15 am and 11 am).

Figure 9 shows *Ilheus* data described also by MFCC. When we employed normalized acoustic indices, similar results were attained. On the right side, spectrograms from near groups are presented. These groups have a predominance of sound patterns of a fish chorus. Moreover, on the left side, the spectrogram represents a group that contains crustacean sounds.

Lastly, Figure 10 depicts *Laje* data described by normalized acoustic indices. Spectrograms on the bottom and right highlight a group with vessel sound patterns. The spectrogram on the top-right represents a group that contains crustacean sounds. Meanwhile, the spectrogram on bottom-left is related to a group with fish sounds, and the one on top-left has sounds of fish and crustacean.

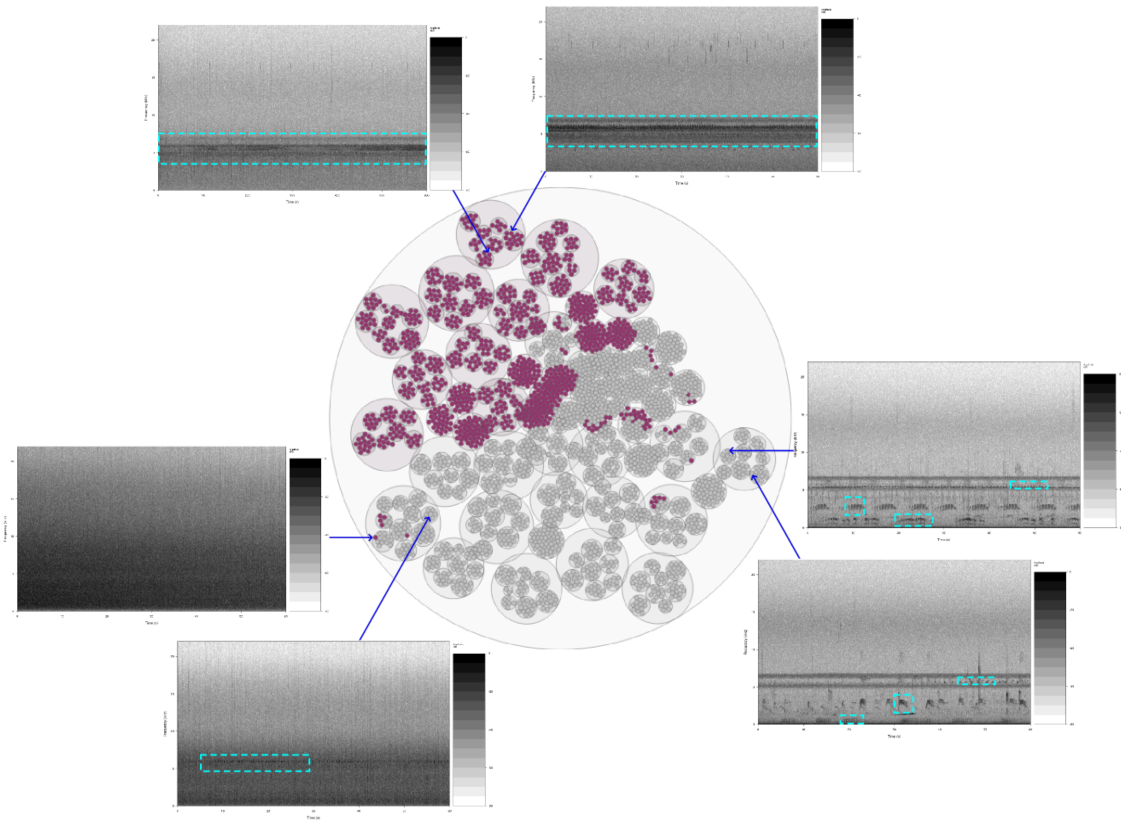

Figure 7: *Costa Rica* data represented by MFCC (without normalization), projected with xHiPP. Point colors are related to CostaRica1 (purple) and CostaRica2 (gray) areas. Some points are highlighted with spectrograms and areas of them are pointed with light-blue boxes to identify audio patterns [10].

6. Discussion

Visual techniques aforementioned are suitable ways to help exploration, analyses, location of both general and specific patterns, and interpretation of ecological information coded by acoustic features. For instance, the statistical information showed by the boxplot aids the analyses and comparison of feature variation inside and among areas.

The distinction of audios with same attributes improve the search of particular sounds and allows the analyst to realize relationships among audios without listening all dataset. With parallel coordinates is possible to compare the behavior of different areas, and identify specifications of each analyzed region.

Information presented with heatmap makes easy the verification of a specific feature behavior. One can examine changes in the acoustic scenario by the variations of a feature related to periods.

The hierarchical layout and the summarising capacities of xHiPP provides a desirable manner to guide users to specific patterns. Thus, they can put their efforts to verify patterns of interest, focusing on the analysis of groups that contain them. For example, one can verify species diversity, sounds that can not stay on preservation areas, and so forth.

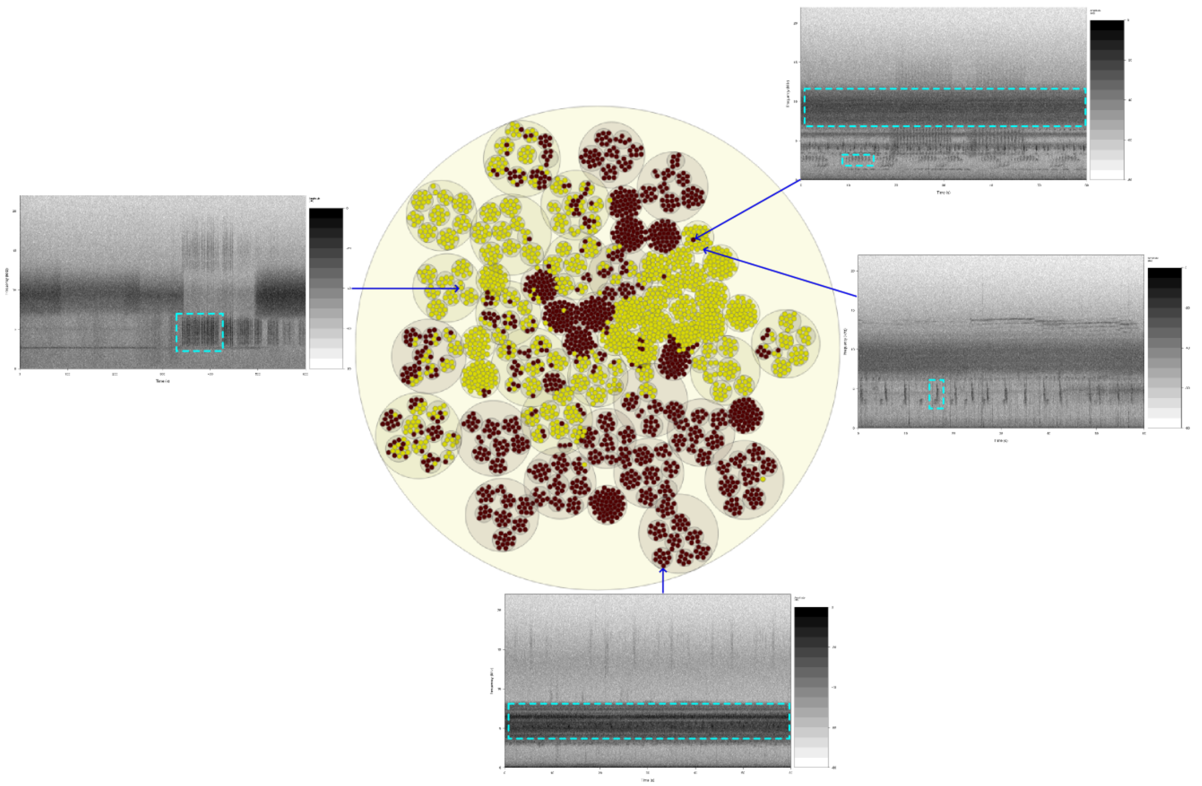

Figure 8: *Costa Rica* data represented by MFCC (without normalization), projected with xHiPP. Point colors are related to daytime (yellow) and nighttime (brown). Some points are highlighted with spectrograms and areas of them are pointed with light-blue boxes to identify audio patterns [10].

These techniques can improve visual approaches cited in Section 3. The evaluation of feature behavior with boxplot, parallel coordinates, and heatmap can aid the definition of suitable features to build the false-color spectrogram proposed by Towsey et al. [2] or the view defined by Sánchez-Gendriz and Padovese [19]. These visualizations can also help the analysis of appropriate features to acoustic segregation, extending Reis et al. [11] studies. Moreover, xHiPP is also suitable for verifying the clustering and visualization goals related to Phillips et al. [5].

Clearly, even that these techniques have good abilities to enhance analysis capability, they have some limitations. The number of features showed by parallel coordinates depends on the screen space and a large number of samples can cause visual clutter. With heatmap, if value variations are small, the color level distinction will be hard. The xHiPP (as other MDP techniques) generates some distortions on feature space.

Despite these limitations, the applied techniques added to the soundscape analysis the ability to separate and effectively locate patterns, beyond the improvement of other exploration techniques. With this, it is possible to determine the acoustic content of a dataset without the time-consuming task of listening to large amount of audio files.

In addition, the application of these techniques depends on the nature of the scenario and the user necessities. For instance, depending on the variation of feature values, with parallel coordinates and boxplot, it will be difficult to figure out distinct patterns. On the other hand, xHiPP can present segregation patterns due to its capacity to represent trends from a combination of features.

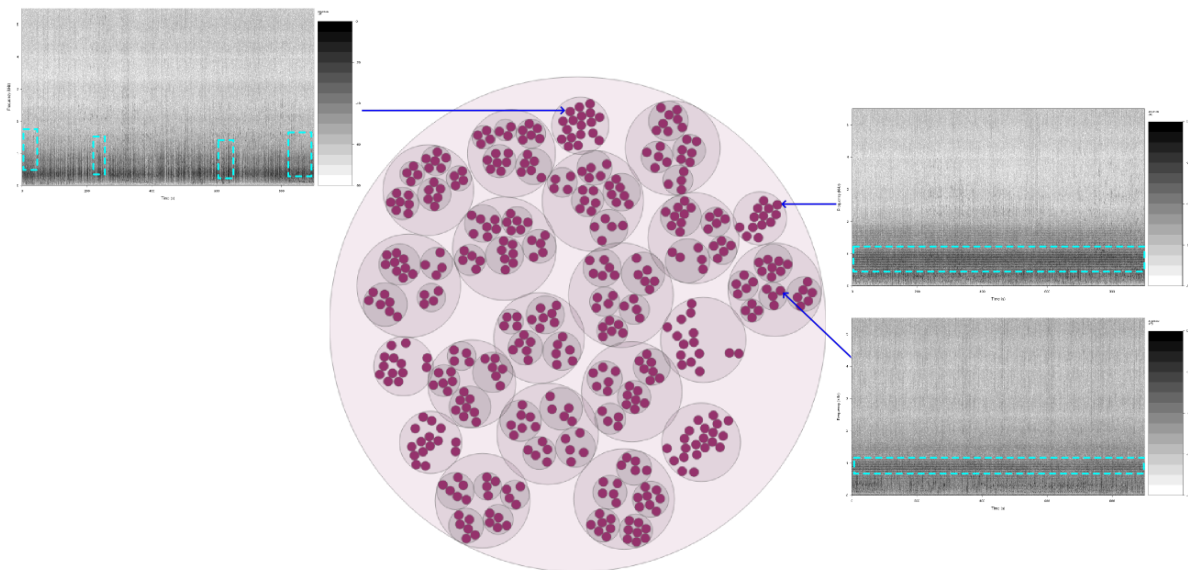

Figure 9: *Ilheus* data represented by MFCC (without normalization), projected with xHiPP. Some points are highlighted with spectrograms and areas of them are pointed with light-blue boxes to identify audio patterns [10].

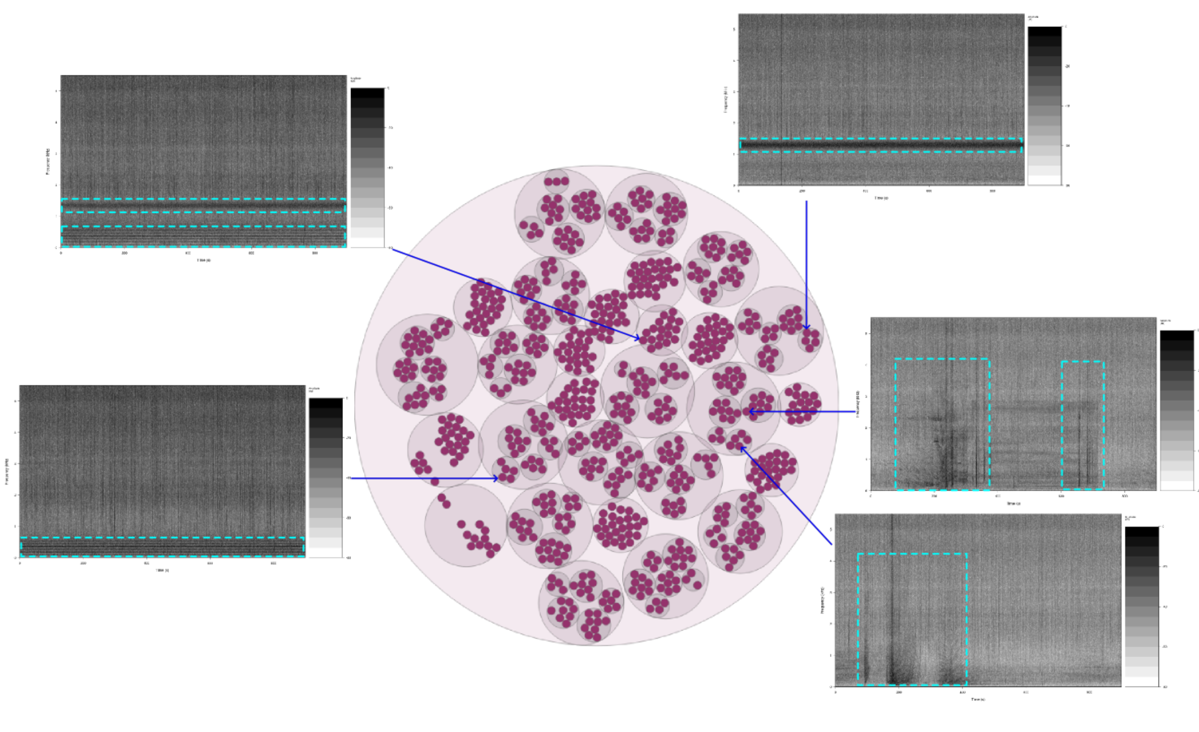

Figure 10: *Laje de Santos* data represented by acoustic indices (with *Min-max* normalization), projected with xHiPP. Some points are highlighted with spectrograms and areas of them are pointed with light-blue boxes to identify audio patterns [10].

7. Conclusions and future work

This report presents a simple process that applies InfoVis tools such as a visual aid to explore audio sets. Boxplots, parallel coordinates, heatmaps, and xHiPP have supported roles in the process. They represent a way of deepening the analysis with the examination of data relationships and attribute values for interesting patterns.

Even if good results become these techniques useful to explore and analyze soundscape data, the limitations aforesaid need to be dialed. Therefore, it is possible to explore other InfoVis techniques that could better manipulate the amount of data; the application of tools that enhance visual capabilities; and the use of other libraries beyond D3.js to implement the codes.

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