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SOUND ENVIRONMENTS CLASSIFICATION OF A UNIVERSITY CAMPUS USING UNSUPERVISED MACHINE LEARNING TECHNIQUES

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ABSTRACT

A university campus, often comparable to a small city, faces similar challenges in monitoring and managing noise pollution within their environments. This study presents a methodology to classify the diverse soundscapes of a university campus using long-term acoustic measurements collected through a network of acoustic sensors. The research was conducted at the Catholic University of San Antonio in Murcia, where sound data was captured and analyzed based on sound pressure levels. In addition to using overall sound pressure levels data, the study explores the advantages and limitations of incorporating more detailed information, such as sound pressure levels segmented by frequency bands, for identifying acoustic patterns. Unsupervised machine learning techniques, specifically the k-means clustering algorithm, were applied to process the extensive dataset generated by continuous monitoring. This methodology facilitated the identification of distinct acoustic patterns across the campus. The results demonstrate the potential of combining acoustic sensor networks with machine learning algorithms to efficiently monitor and categorize urban-like environments such as university campuses. This approach provides a scalable and cost-effective solution for soundscape management, while highlighting the potential benefits of integrating more granular acoustic data for enhanced pattern recognition.

Keywords: *soundscape, university campus, sound pressure level, IoT, monitoring*

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1. INTRODUCTION

The contemporary university campus presents a complex acoustic environment where diverse sound sources, ranging from human activities to transportation noise, affect both outdoor and indoor soundscapes [1], [2]. The soundscape of university environment plays a pivotal role in influencing students' well-being, cognitive performance, and academic satisfaction [3]. Furthermore, in recent years, the concept of soundscape has gained increasing relevance in the design and management of campus environments [4].

The implementation of Wireless Acoustic Sensor Networks (WASN) has revolutionized acoustic monitoring methodologies by providing systems for real-time data collection and transmission in a distributed and scalable manner [2]. These networks enable a more precise and dynamic characterization of soundscapes, facilitating the detection of relevant acoustic events and the spatial and temporal analysis of noise. The measurement of sound pressure level (SPL) serves as a fundamental indicator to characterize acoustic environment and evaluate exposure to noise and its potential health impacts [5]. Despite its widespread use, conventional approaches to noise assessment typically emphasize the average SPL values, which can overlook the intricate temporal and spatial fluctuations present in complex soundscapes.

To address these shortcomings, unsupervised machine learning methods, such as k-means clustering, have gained traction as effective strategies for analyzing large acoustic datasets. These techniques allow for the automatic grouping of sound pressure data into clusters that exhibit similar properties, thereby facilitating the discovery of distinct noise patterns and acoustic zones that traditional methods might miss.

This paper is focused on evaluating the suitability of applying a WASN-based system for long-term temporal monitoring of acustics parameters in order to assess the acoustic environment in a High Education institutions for this purpose. This work explores the integration of unsupervised machine learning techniques, specifically k-means clustering, for analyzing SPL data in complex environments, with the aim of enhancing noise management strategies and improving acoustic comfort.

2. MATERIALS AND METHODOLOGY

This smart campus initiative involves the design and implementation of WASN strategically placed at various indoor and outdoor locations. For this work, four sensor nodes are deployed, one of then are located outdoor. The outdoor area is a highly frequented space utilized by staff and students during break periods and for hosting special events such as forums and exhibitions. Consequently, it serves as an open venue for the entire university community, with the primary source of noise being predominantly anthropogenic. While the rest of nodes are indoors, in particular, an office, a classroom and an entrance hall.

Each WASN is capable of continuously acquiring valuable acoustic data over extended periods. Each node is equipped with sensors for capturing sound signals, and calculating acoustic metric such as the sound pressure level (SPL) in dB, along with the SPL values in several octave frequency bands (dB), specifically 125 Hz band, 250 Hz band, 1 kHz band, 2 kHz band, 4 kHz band. Moreover, As well as embedded software for processing audio inputs and computing key acoustic parameters.

Monitoring is performed for four months, twenty four hours per day, with data capture every minute in different scenarios.

For the input data, no preprocessing or aggregation is applied; thus, the model's input consists solely of the metrics corresponding to the octave frequency bands.

Subsequently, the collected data are analyzed, preprocessed, and cleaned to ensure quality and reliability. Once the data is properly prepared, it is utilized in an unsupervised learning approach using the k-means clustering algorithm, For a given value of k, k-means algorithm groups the nodes in k-clusters. This technique enables the identification of homogeneous groups within the dataset, thereby facilitating the classification of different acoustic environmental sound patterns. Where the parameter K denotes the predetermined number of clusters specified prior to the execution of the algorithm, guiding the iterative assignment of data points to the nearest cluster centroid based on a defined distance metric.

The algorithm iterates in two steps until the centroids have stabilized. In the first stage of the process, known as the assignment step, each node is associated with the closest centroid according to the computed distance. The second step, known as the update phase, involves recalculating the centroid positions by determining the element-wise arithmetic mean of all data points associated with each cluster [6].

Software and Technology

Data preparation, transformation, analysis, and modeling were carried out using the open-source programming language R [7], version 4.3.2. The computational environment included an AMD Ryzen 7 5800X 8-core processor running at 3.80 GHz, 32 GB of RAM, and an Nvidia GTX 3050 GPU with 8 GB GDDR6 memory. The analysis utilized several R libraries: dplyr (version 1.1.4), lubridate (version 1.9.3), tidyr (version 1.3.0), cluster (version 2.1.4), clValid (version 0.7), mclust (version 6.1.1), Kohonen (version 3.0.12) and ggplot2 (version 3.4.4). To ensure the reproducibility of results, a fixed seed was set using the `set.seed()` function for all tasks involving random processes. Furthermore, given the changes in random number generation introduced in R version 4.0.0, additional steps were taken to standardize the methodology and guarantee consistent outcomes across different R versions.

3. RESULTS AND DISCUSSION

In this section, results obtained from applying the clustering technique, K-means, to the collected data are analyzed and discussed.

To determinate the appropriate amount of clusters, k-means algorithm has been trained for k = 1, . . . , 12, being this one with 5 clusters the best of them for Silhouette metric [8]. Therefore, the model has been trained with k=5, as it maximizes the Silhouette. This indicates that clusters of sounds are formed based on their similar behavior with respect to the five selected variables, namely, the SPL in several octave frequency bands, i.e. from 125 Hz to 4,000 Hz. Centroids, in dB, are calculated according to [9].

Tab. 1 shows the clusters' centroids created by clustering.

The data obtained allow for the identification of multiple sound sources impacting the acoustic environment of

Table 1. Centroid of clusters using data collected during monitoring the university.

Group	125 Hz band	250 Hz band	1 kHz band	2 kHz band	4 kHz band	Colour
1	32.94	30.20	23.97	21.11	18.45	black
2	36.72	18.29	18.28	48.81	24.57	pink
3	39.53	38.55	33.43	26.68	22.84	cyan
4	51.32	43.08	40.77	31.81	30.02	brown
5	56.32	47.38	48.13	54.76	33.72	blue

the university.

Group 1 shows a constant decreasing trend from 125 Hz band to 4 kHz band.This reduction suggests a predominance of low-frequency sound sources, potentially associated with structure-borne noise. Additionally, the presence of furniture in the area may contribute to acoustic absorption, while the attenuation of high frequencies indicates that they are being absorbed or dispersed within the environment.

Group 2 has a sharp drop at 250 Hz band, staying at low values until 1 kHz band.Then, at 2 kHz band, it experiences a sharp peak before dropping again at 4 kHz band.This suggests that this group is very sensitive to certain frequencies, especially in the 2 kHz region, where the dB level is the highest.

Group 3 also presents a progressive reduction in dB, although less pronounced than group 1.

Group 4 exhibits a higher value in the 125 Hz frequency band, suggesting the influence of ventilation systems and structure-borne noise.

Group 5 highlights two frequency bands: 2 kHz frequency band and 125 Hz frequency band. This cluster represents an outdoor node where students gather on benches during breaks. The 2 kHz frequency band is associated with human speech, indicating that conversations significantly contribute to the acoustic environment in this area. Meanwhile, the 125 Hz frequency band component is influenced by its proximity to the transportation zone, where external noise sources, such as vehicle traffic, play a role.

The values obtained from the Tab. 1 are represented in Figure 1, which illustrates the variation in dBA levels across different frequency bands for distinct groups.

Group 3 and 5 have peaks in 2 kHz band, suggesting that this band has a greater impact in certain scenarios.

Group 1 and 2 show a downward trend, which may be related to energy loss at high frequencies.

In order to show the relevance and the relation between these indicators 125 Hz Band, 250 Hz band, 1 kHz band, 2 kHz band and 4 kHz band. A smoothed color density scatterplot representing all monitoring can be seen in

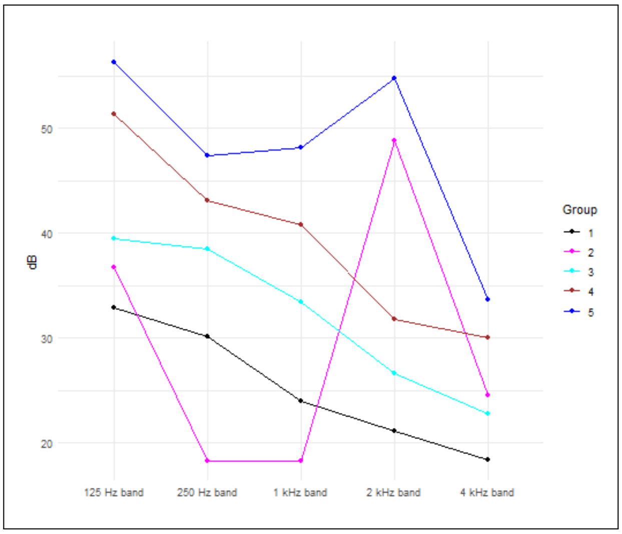

Figure 1. Centroids according to cluster and their respective frequency bands.

Figure 2. The smoothed color density helps to identify dense zones that groups nodes with similar behavior.

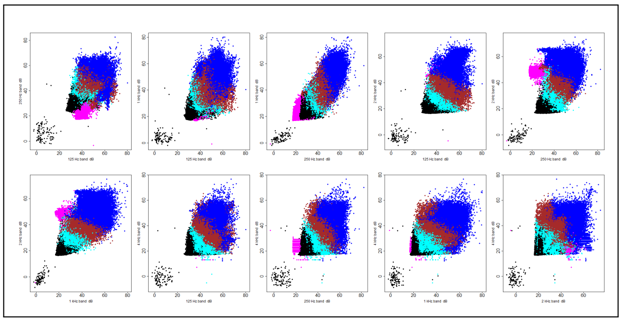

Figure 2. Scatter plot of the 125 Hz band, 250 Hz band, 1 kHz band, 2 kHz band and 4 kHz band metrics representing all time frames.

4. CONCLUSIONS

The acoustic environment within a university setting should be continuously monitored, as various sound sources can significantly impact the well-being and academic performance of the university community. WASN represents an effective tool for environmental acoustic monitoring, enabling the collection of large volumes of data. However, due to the magnitude of the captured information, conventional data processing methods may be insufficient. To address this challenge, the implementation of machine learning algorithms allows for data analysis, pattern recognition, predictive modeling, and the extraction of meaningful insights, enhancing decision-making in acoustic management.

This study presents a preliminary analysis of an urban acoustic environment within a university setting, employing unsupervised machine learning techniques, specifically the k-means clustering algorithm to determine whether the analysis of the values obtained from sound pressure level bands allows for the identification of specific acoustic characteristics. This technique is a good tool for analyzing large amounts of data obtained from the monitoring of sound environments. According to the data obtained, higher SPL values are observed in the low frequency values, 125 Hz band, which present higher SPL than at higher frequencies, Based on the obtained data, it is valid for identifying different sound sources that impact the university environment. In future projects, subjective values such as loudness and sharpness will be added in order to know the correlation that may exist with the band values and to be able to know how these sources are affected.

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