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CLASSIFICATION OF BIOLOGICAL SOUNDS USING SPATIAL DIRECTIVITY

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ABSTRACT*

Bioacoustic methods for biodiversity monitoring face limitations, particularly when relying on single-channel recordings, that lack spatial context. To address this, we tested a novel approach that incorporates spatial directivity into biological sound classification using a network of microphone arrays. Each array, comprising of four microphones, estimates the Direction Of sound Arrival (DOA), attributing spatial features to sound events. By combining these spatial features with conventional acoustic features, in combination with unconventional use of K-means clustering, we developed a methodology for classifying biological sound events. Our approach employs iterative adjustment of the number of clusters to refine classification, filter out noise (e.g., traffic), and reveal tree-like class structures that separate between species and even individuals within same species. Experimental data from a multi-day field recording using synchronized 8-channel microphone systems demonstrates the method's ability to separate sound events and identify individual organisms. The results highlight the potential of spatially informed acoustic analysis to overcome some limitations of bioacousticaly based diversity assessment.

Keywords: *Direction Of Arrival, Sound Event Classification, Bioacoustics, Microphone Array, K-Means, PCA analysys, Sound signal features***.**

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1. INTRODUCTION

In recent years, bioacoustic monitoring has emerged as an essential tool for assessing biodiversity, particularly in ecosystems where visual observation is limited or impractical. Acoustic signals generated by insects, amphibians, birds, and mammals provide rich information that can be used to estimate biodiversity, identify ecological changes, and support conservation efforts [1,2]. While the development of passive acoustic monitoring systems has enabled long-term, non-invasive data collection, the accurate classification of biological sound events remains a significant challenge. In many environments, the acoustic landscape is also heavily contaminated with anthropogenic noise sources such as traffic, aircraft, and industry noise [3]. These noise sources contaminate biologically relevant acoustic signals, reducing the effectiveness of automated classification. Traditional sound classification methods rely heavily on spectral features (e.g., energy levels at specific frequencies), temporal characteristics, and time-frequency representations such as spectrograms [4,5]. However, these approaches often fall short when biologically similar signals, such as calls from different individuals of the same species, exhibit overlapping frequency content. In such cases, additional information is required to improve classification accuracy. Promising and underexplored direction in acoustic monitoring is the use of spatial directivity. i.e. the direction from which sound event originates and how it changes over time. Direction Of sound Arrival (DOA), typically employed in microphone arrays, offers the ability to extract spatial features associated with sound sources [6,7]. This can be particularly useful in field conditions where multiple individuals of the same species are active simultaneously, or where moving sources produce time-varying spatial signatures.

In this study, we investigate the potential of combining conventional acoustic features with spatial directivity features for the classification of biological sound events, with a focus on insect species, specifically crickets. We hypothesize that spatial features such as mean direction, deviation of direction, and imaginary/real components of DOA vectors, when added to standard spectral features, can improve the separation between different individuals, even within the same species, under real environmental conditions. The proposed methodology is based on K-means algorithm with adaptive number of classes for unsupervised feature evaluation and classification. The aim is to develop a framework for distinguishing biologically relevant events from background noise, and for assessing biodiversity by estimating the number and identity of individual signal sources. By integrating spatial analysis into the bioacoustic feature space, this work contributes a novel perspective to acoustic biodiversity monitoring, particularly in complex and noisy environments. The results may have practical implications for automated species detection, behavioral studies, and long-term ecological assessments in increasingly urbanized and acoustically polluted habitats.

2. EXPERIMENTAL SETUP

2.1 Study Site and Recording Conditions

The selected study site is located in Zaplana, a rural area in Slovenia that offers stable infrastructure for long-term acoustic monitoring. This location was chosen primarily due to access to continuous electrical power, reliable on-site supervision, and controlled environmental conditions that minimize the risk of equipment damage or theft. The site provides a natural acoustic environment yet is close enough to human activity to also include anthropogenic noise, which is important for the development of separation techniques, as shown in Figure 1.

Figure 1: Data acquisition location with measurement systems

Eight Behringer ECM8000 measurement microphones, selected for their flat frequency response and omnidirectional pickup pattern, which are well suited for capturing complex environmental soundscapes. Four microphones, forming one system, were spatially distributed in a square array of 40mm, optimized for Direction Of Arrival (DOA) calculations in frequency range from 60 to 6000 Hz. Two systems, i.e. arrays, were used.
All eight microphones were connected to a MOTU Stage B 16-channel stage microphone preamplifier, with integrated AD converter and USB3 connection. Such a setup ensured phase-synchronized signal acquisition across all channels, a prerequisite for subsequent beamforming and directionality analysis. The AD converter was connected to a custom LabVIEW-based acquisition system that managed signal recording and real-time data processing. The software was developed in-house to enable robust control over file handling, signal normalization, and metadata logging.
The microphone array and hardware were housed in weather-protected enclosures and mounted at fixed positions throughout the measurement campaign to maintain geometric stability. The entire system operated autonomously over the 36-hour recording period, powered by the site's reliable local electricity supply, with occasional human supervision for maintenance and monitoring. Recordings were acquired in 30-second intervals, with a pause of 5 to 10 seconds between each segment due to WAV file saving time to disk. This led to the generation of 3880 multi-channel WAV files, each containing eight synchronized audio channels. Such temporal segmentation was a compromise between disk write speed and uninterrupted monitoring, and it ensured sufficient data quality for post-hoc feature extraction and classification analysis.

2.2 Signal Processing and Feature Extraction

A major challenge in biodiversity acoustics is the extraction of meaningful information from large volumes of long-term, multichannel audio recordings. The aim of this study was to identify and classify biological acoustic events using both spectral and spatial characteristics of sound. The following signal processing steps were implemented to transform raw waveform data into a structured set of acoustic features suitable for classification.

2.2.1 Data Preprocessing

The raw recordings consisted of 30-second-long multichannel WAV files. Due to constraints in disk writing speed, a gap of 5 to 10 seconds existed between consecutive files, resulting in discontinuous but time-stamped data. Each recording contained eight synchronously recorded channels, enabling spatial analysis. All recordings were preprocessed using the custom LabVIEW-based software developed specifically for this application. Preprocessing included: Amplitude normalization of all signals to the same reference level, DC offset removal, Segmentation of the recordings into fixed intervals for time-aligned feature extraction, Filtering for optional band-limiting to biologically relevant frequency ranges.

2.2.2 Feature Extraction

Feature extraction was performed for each segment and on each channel independently unless otherwise specified. A total of over 100 acoustic features were computed, categorized into the following domains:

Spectral Features: including power spectral densities across third-octave bands, dominant frequency, spectral centroid, spectral roll-off, skewness and kurtosis of the normalized spectrum.

Cepstral Features: calculated from the real cepstrum of each segment, including the frequency and amplitude of the dominant peak, the cepstral centroid, and energy measures.

Time Domain Features: such as zero crossing rate, short-term signal energy, crest factor, skewness and kurtosis of the waveform, and amplitude envelope characteristics.

Autocorrelation Features: including number of zero crossings of the autocorrelation function, integral properties of its shape, and geometric descriptors (e.g., string length of normalized autocorrelation curve).

Spatial Features: derived from direction-of-arrival (DOA) estimation algorithms applied to the microphone array data. These included average and deviation of real and imaginary DOA components, and instantaneous DOA angle estimation using phase-difference methods.

Each feature was computed within a 125 ms time window with no overlapping, selected as a compromise between temporal resolution and stability of DOA and spectral statistics. Importantly, the spatial features were calculated from twelve DOA snapshots within each 125 ms frame, to account for the rapid directional fluctuations in low-SNR conditions.

2.2.3 2.3.3 Feature Selection and Dimensionality Reduction

Given the high dimensionality of the feature space, a series of statistical techniques were employed to reduce redundancy and highlight relevant dimensions for classification. These included:

- Principal Component Analysis (PCA) to identify dominant modes of variance,
- Singular Value Decomposition (SVD) to rank feature importance,
- Correlation analysis to remove colinear features,
- Expert-driven selection, particularly for features known to be relevant for distinguishing between insect species (e.g., 2576 Hz and 8000 Hz bands).

The final feature set used in classification experiments typically consisted of 4 to 6 features, balancing interpretability with classification accuracy. These included a mix of spectral bands, signal shape descriptors, and spatial DOA deviations. The extracted features formed the basis for further analyses, including unsupervised clustering (K-means) and biodiversity assessment discussed in the next section.

2.3 K-Means Classification

Unsupervised K-means classification algorithm was selected to assess the separability of different types of sound events and to support biodiversity monitoring. This method partitions the dataset into a specified number of clusters by minimizing the within-cluster variance and is widely used for its efficiency and interpretability of data [16].

In our study, a selected subset of features was used as input for clustering. These included both classical acoustic features such as signal energy levels at selected frequencies (e.g., 2576 Hz and 8000 Hz) and temporal characteristics (e.g., zero crossing rate), as well as spatial features related to the direction of arrival (DOA) and its variability.

The initial number of clusters was estimated using the Elbow method, which plots the within-cluster sum of squares (WCSS) against the number of clusters. A visible 'elbow' in the curve typically indicates the appropriate number of clusters. This method was implemented using MATLAB. In our data, the elbow typically occurred between 4 and 6 clusters. Initial results showed that traffic noise and biological signals often clustered separately, confirming that classical spectral features are sufficient to isolate low-frequency anthropogenic noise. Further subdivision of clusters revealed differences between different insect species calls.

An interesting aspect of the approach was the tree-like splitting of clusters when the number of clusters gradually increased. For instance, starting with three clusters often separated background, traffic, and biological signals. Increasing to five or six clusters revealed distinctions between insects. This exploratory method provided insights into both the structure of the dataset and the potential for unsupervised identification of acoustic diversity in the environment.

These findings highlight that unsupervised learning, when guided by expert's selected feature vector, can serve as a robust tool for separating meaningful acoustic events from environmental noise.

3. RESULTS

To better illustrate the challenges associated with classifying biological sounds in natural environments, Figure 2 presents a representative 10-second recording from two spatially separated microphone array systems, located 12 meters apart. Figure 2 shows the spectrograms for both systems (top and bottom panels) alongside the corresponding Direction of Arrival (DOA) estimates over time. DOA results are plotted between the two spectrograms, with red dots representing System 2 and blue dots representing System 1. DOA calculations were performed on filtered signals, using a band-pass filter (2000–4000 Hz) to isolate the frequency range of interest, the calling frequencies of cricket of species A. This filtering helps suppress environmental noise and focuses on the DOA of crickets. Accurate DOA tracking corresponds with cricket calls, while scattered DOA values appear during silent intervals.

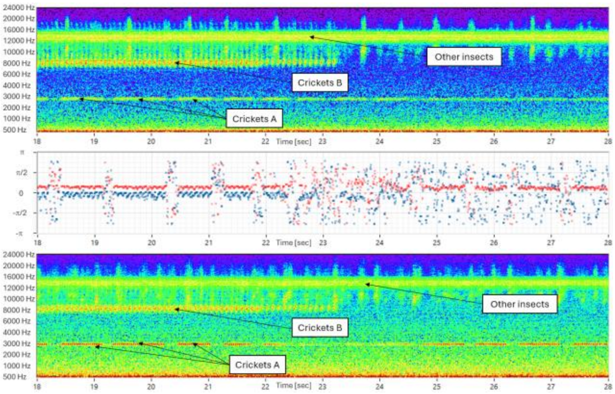

Figure 2: Example of a 10-second recording showing spectrograms of two synchronized microphone systems placed 12 meters apart. Red and blue dots represent DOA estimates from System 1 and System 2, respectively, in the 2000–4000 Hz range, specificly tuned to detect crickets of species A.

The visualization demonstrates that when a cricket is actively producing sound, the DOA algorithm accurately tracks its spatial position. However, during silent periods or low signal-to-noise conditions, the system yields scattered direction estimates with high deviation, suggesting that direction estimates are essentially random in the absence of a clear signal. This behavior underlines one of the key limitations of DOA based approaches in natural environments: direction estimation requires some minimal signal to noise ratio to be reliable.
An additional challenge is the temporal structure of cricket calls. Each call (approximately 1 second in duration) consists of a sequence of 12–30 short chirps, each lasting only a few milliseconds. These brief chirps are separated by short pauses. During these pauses, the DOA algorithm frequently registers spurious directions due to the lack of acoustic energy, which cannot be easily averaged due to the circular nature of angular data. This causes angular "jumps" or artifacts, making the differentiation between multiple crickets of the same species particularly challenging.
Despite these limitations, the system shows strong potential for spatially resolving biologically relevant sounds. This example sets the stage for the subsequent sections, which evaluate various feature extraction methods and classification strategies, including unsupervised learning.

3.1 PCA Analysis of the Whole Dataset

To assess the relative contribution of features in the dataset and to identify dominant patterns of variability, we performed principal component analysis (PCA) on the full dataset, comprising 108 features extracted from synchronized 8-channel acoustic recordings. Prior to the analysis, all features were normalized using min-max scaling to the [0,1] range.
This ensured that features of differing physical dimensions (e.g., signal amplitude, spectral centroid, direction deviation) contributed comparably to the analysis. PCA was then performed on the normalized dataset. The first principal component (PC1) alone explains approximately 30% of the total variance, while the first two components together account for more than 50%.

3.1.1 Feature Contributions to PC1

By examining the loadings of each feature on PC1, we can identify which features contribute most to this dominant source of variance. Among the most influential features were zero crossing rate, and its two derivatives (crossing at 0.125 and 0.25), high-frequency spectral components (e.g., 15608 Hz, 13664 Hz), and spectral centroid. Zero crosing of Autocorelation function and Cepstrum based features also proved to be important. Spatial features extracted during DOA calculation however showed only moderate influence.
The PCA results support our hypothesis that a combination of signal energy, zero-crossing, and spatial features collectively governs the variance in the overal acoustic dataset. Notably, individual frequency bands used for species classification (e.g., 2576 Hz and 8000 Hz) did not emerge as dominant contributors in PC1. This reinforces the need to integrate spatial directivity metrics when aiming to distinguish between acoustically similar species or individuals. These findings suggest that both spectral and

temporal discontinuity features are key discriminators in the data. However, the moderate loadings of spatial features also imply their relevance, particularly for distinguishing between individual sources of similar spectral character.

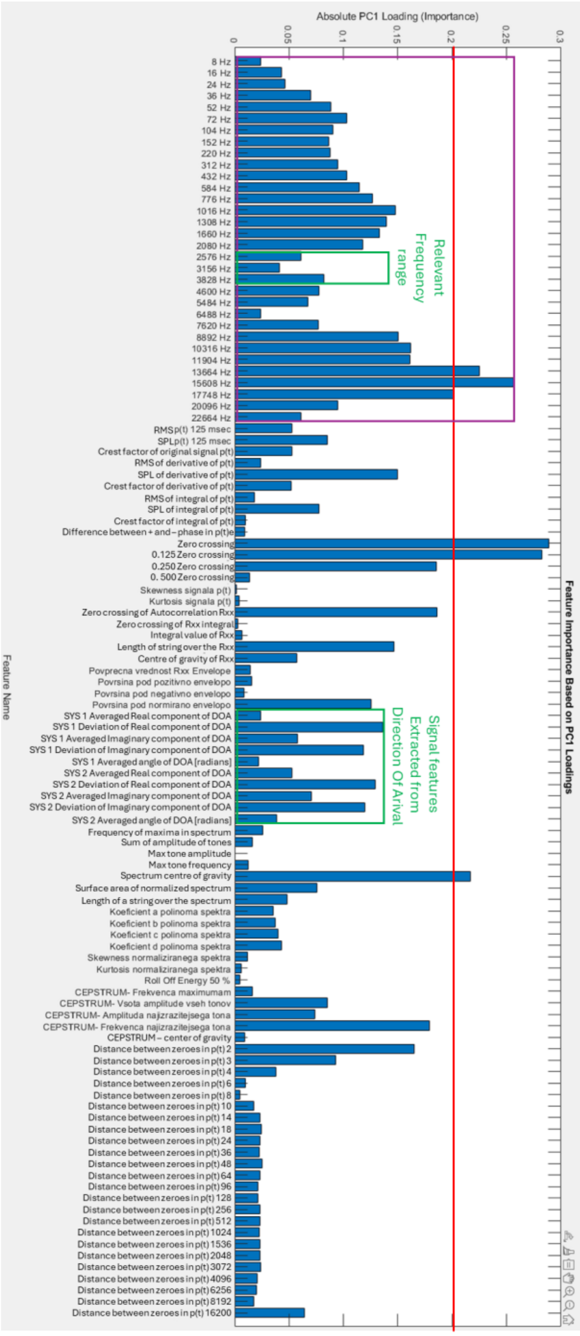

Figure 3: Bar chart of absolute PC1 loadings for all features

3.1.2 Subjective Feature Selection

Following the initial inspection of the recordings and DOA behavior, we performed a subjective selection of features for the unsupervised classification. Subjective approach was motivated by our experience, by the structural complexity of crickets calls, and the known limitations of automated feature selection methods in low signal-to-noise environments. To reduce data dimensionality while preserving relevant information, we selected a subset of features: from the complete dataset based on three criteria: (1) domain knowledge about cricket call characteristics, (2) visual correlation of features with known biological events (e.g., active chirping), and (3) interpretability and temporal stability of the feature across multiple recordings. The following eight features were chosen for initial analysis:

Level of signal derivative (captures abrupt energy changes in short-duration chirps)

1. Level at 2576 Hz
2. Level at 8000 Hz
3. Direction Of Arrival on System 1
4. Deviation of DOA on System 1
5. Direction Of Arrival on System 2
6. Deviation of DOA on System 2
7. Zero Crossing Rate (ZCR),

These features were selected not only for their statistical relevance but also for their interpretability. For example, signal derivative and zero-crossing features respond to the pulse-like nature of chirps, while DOA deviation provides a strong inverse indicator of consistent sound sources (i.e., crickets). Frequency-specific features were chosen to separate overlapping frequency bands used by different species. The subjective selection was further validated through data visualization and initial clustering tests. This manual step proved essential in capturing meaningful biological structure in a highly complex acoustic environmet.

3.2 K-Means Clustering

Several established methods exist to estimate the "optimal" number of clusters in K-means clustering, including the elbow method (which identifies a knee in the within-cluster sum of squares), silhouette analysis, and the gap statistic. More advanced criteria such as the Calinski-Harabasz, Davies-Bouldin, and Dunn indices, or model-based tools like Bayesian Information Criterion (BIC), are frequently employed in automatic model selection.

However, in the context of bioacoustic field recordings, these methods proved insufficient. They consistently suggested a relatively small number of clusters (typically fewer than six), which did not reflect the nuanced structure of the biological acoustic environment. In our case, the goal was not to discover a fixed, singular classification scheme, but to explore the hierarchical relationships between sound events, and incrementally refine the detection and separation of biological signals from environmental noise.

To that end, we adopted a progressive and semi-supervised clustering approach. Starting with a subset of recordings that contained known biological activity (observed directly during data collection), we applied K-means repeatedly, increasing the number of clusters step by step. This revealed a tree-like evolution of classes, where larger clusters gradually split into finer subgroups as the number of clusters increased. Importantly, this process exposed meaningful patterns:

- A small number of clusters (e.g., k = 2–3), K-means already separates high-energy signals, such as traffic noise, from ambient biological sounds.
- As the number of clusters increased (k > 5), we began to see separation between different types of biological signals, including cricket chirps of different species, and eventually between individual crickets of the same species based on spatial and temporal features.

Figure 4 demonstrates how the separation between traffic noise and biological signals improves with an increasing number of classes, specifically in the context of filtering out peaks (e.g., traffic) while preserving fluctuating ambient sounds (e.g., insects). Based on this insight we structured our classification process into three stages as depicted in a series of figures from Figure 5 to 9.

1) Noise Filtering: Low-frequency traffic noise was excluded from the data based on spectral and temporal features. Consequently, higher-frequency traffic noise overlaping bioacoustic sound was removed as well.

2) Species Identification: By selecting key spectral features (SPL at 2576 Hz and 8000 Hz) we were able to distinguish between cricket of species A and B. Narrowband filtering alone was insufficient; classification relied on the overall feature vector and clustering behavior.

3) Individual Discrimination via DOA: By incorporating spatial features of direction of arrival (DOA) and deviation of DOA, K-means could distinguish signals from different individuals of the same species A, even when their spectral profiles were similar.

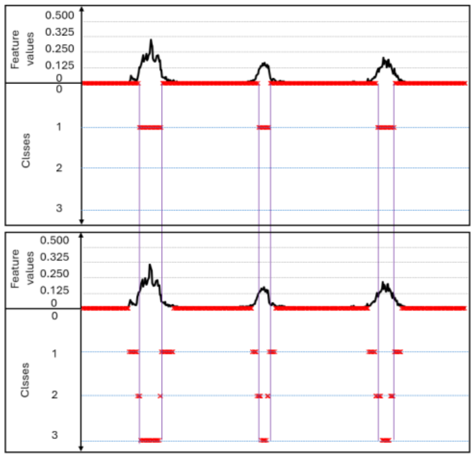

Figure 4: By increasing the number of classes in K-Means algorithm, the separation between background noise and signal is more effective. In our case we are interested into exclusion of pulses, representing traffic noise and to maintain background noise composed from biological sounds.

The presented approach effectively combines unsupervised clustering with subsequent supervised refinement, allowing us to separate traffic noise from biological signals and then further differentiate among species or members of species based on sound directivity data (DOA). The gradual increase in the number of clusters to form a tree-like structure is particularly insightful, as it provides a visual and quantitative means to identify the minimal number of classes required for effective discrimination. This multi-step process, first filtering out traffic noise, then distinguishing species based on spectral features, and finally resolving individual variation using spatial features, demonstrates a robust strategy for addressing the complexities inherent in bioacoustics data.

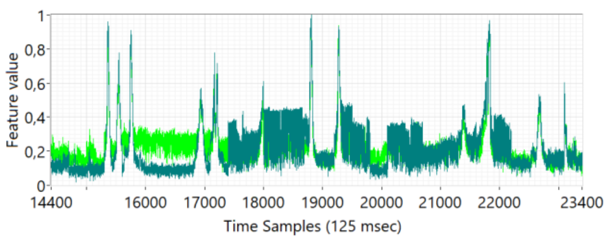

Figure 5: Recorded signal @ 2576 Hz and 8000 Hz, with pronounced spikes due to the traffic noise

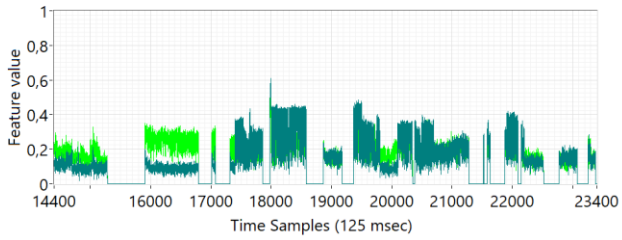

Figure 6: The first step: Exclusion of unappropriate samples, containing traffic noise 2576 Hz and 8000 Hz, that is in frequency range of cricket's calls.

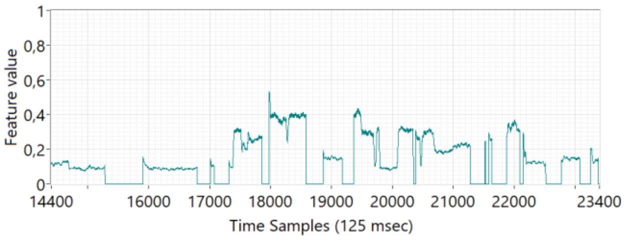

Figure 7: Second step was to smooth the data by moving average, while maintaining the exclusion of corrupted data by traffic noise

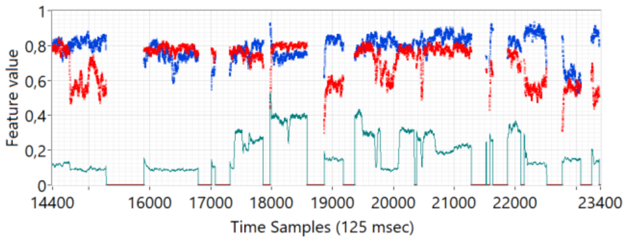

Figure 8: Third step was to implement the spatial directivity (DOA) from two systems into the classsification

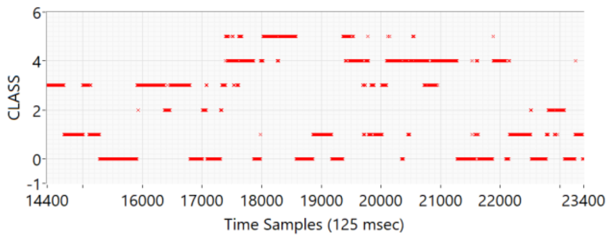

Figure 9: Results of Classification to 6 clases (evaluated by the elboww method) and using subjectivly selected features.. Classification includes DOA based features, hence classification of biological sounds using spatial directivity.

The use of K-means clustering in this study extended beyond traditional unsupervised classification. Through iterative refinement and adaptive manipulation of the number of clusters, we were able to explore the latent structure in the dataset and identify practical thresholds for signal separation. Notably, K-means classification was not only used as a final output but also as a tool for feature selection and filtering—enabling us to progressively refine the data by first removing traffic noise and later isolating biologically relevant events.

Despite promising results, some limitations were encountered. While spatial directivity (DOA) features significantly contributed to distinguishing individual sources, they were insufficient on their own for the complete classification of cricket species. Chirp structure and signal continuity played a crucial role in DOA reliability. The DOA subwindowing approach proved sensitive to brief signal gaps within cricket chirps, leading to erratic directional estimates during the pauses. This reduced the classification resolution and introduced variability into the spatial feature set.

A key insight from these challenges is the importance of synchronization between signal segmentation and DOA estimation. Future work should focus on optimizing the trade-off between subwindow duration and averaging period during feature extraction. For example, preliminary tests suggest that using a 25 ms subwindow and averaging over 250 ms may offer a better balance between time resolution and directional stability than the currently used 10 ms / 120 ms configuration. This will be crucial for capturing species-specific calling patterns while preserving spatial integrity.

Nonetheless, the integration of spatial features, particularly deviation metrics, demonstrated clear value in enhancing the separability of overlapping sound sources, especially for individuals within the same species. This directionally informed classification represents a novel addition to conventional bioacoustic methods, which often rely solely on spectral or temporal descriptors.

4. CONCLUSION

This study presents a novel approach to the classification of biological sounds by integrating spatial directivity information into the feature set. We demonstrated that alternative applications of unsupervised K-means classification algorithm, by iterative clustering with different number of classes can improve classification accuracy in complex outdoor acoustic environments.

We found that spatial features, particularly DOA and deviation of DOA within 125 msec, can successfully add information to traditional spectral features. While direct classification based solely on DOA remains challenging due to signal intermittency, combining directionality with

spectral features enables the identification of both species and individual callers in limited range.
This integrative methodology offers a promising framework for scalable, autonomous biodiversity monitoring, particularly in habitats affected by overlapping biological and anthropogenic sounds. The results not only highlight the potential of spatial information in bioacoustics but also lay the groundwork for future improvements in sensor design, feature synchronization, and hybrid supervised-unsupervised classification strategies.
With further development, such techniques may significantly advance acoustic biodiversity assessment, contributing to conservation science, species tracking, and real-time ecosystem monitoring.

5. ACKNOWLEDGMENTS

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