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Insects Sound Classification with Acoustic Features and k-Nearest Algorithm

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Abstract: Monitoring particular species and the health of the entire ecosystem necessities determining the existence and number of insects. Several insects are easily detected by their sounds, and thus, passive MFCC checking is appropriate. However, practical constraints including the requirement for a human setting, dependency on example sound libraries, low accuracy, robustness, and low ability to generalize to MFCC situations frequently prevent the advancement of MFCC monitoring. Here, report outcomes from collaborative data. The study has utilized improved MFCC scanning datasets, summarizes the machine learning methods, and carry out extensive performance analysis. The study includes different machine learning models and the study has found 85.4% accuracy from K nearest neighbor method. In the future, this study will be extended to remote monitoring projects. The study also needs to validate more sound features with the help of modern artificial intelligence models.

Keywords - MFCC features · MFCC signatures, Insect Sound, K nearest Algorithm

1.0 Introduction

Insect activities(Phung,2017) include many other activities apart from feeding, moving, scraping, crawling, flying, and singing. These activities are sources of sound frequencies from which one can get to know the species of an insect. This implies that each insect sound might have its own distinct set of MFCC characteristics acting as a trademark. The System has the potential to provide automatic monitoring, a technique for spotting insect activity, even though it's concealed in seeds. Australia's Edith Cowan University is in Perth. Numerous MFCC devices have been created and released on the market to automate the detecting procedure.. Numerous variables, including the frequency range and sensor types (piezoelectric transducers, ultrasonic sensors, accelerometers), affect how well acoustic devices perform. It also relies on propagation medium (air, wood, grain, etc.), the volume of the sound, separation between sensor and insect, and other factors The devices were developed to detect insect frequencies produced in particular areas, e.g. wood, soil, or air. Since insect signals are frequently wideband, detectability is highly dependent on the interface between the sensor and the area. This study tested various MFCC feature sets of sounds produced by insects' activities to investigate a wider spectrum of insect detection. To extract MFCC properties in the temporal and frequency domains, we analyzed sound samples of several insects that are known to exist with MFCC features in both time and frequency domains. The accuracy of insect detection was then assessed using a variety of classifiers, it includes the Support Vector Machine, the KNN (K-Nearest-Neighbor), the LD (Linear Discriminant).

2 MFCC Features :

Insect activities are uncertain and vary for each insect, therefore, the key challenge in MFCC insect detection(Chen,2014) so that machine learning(Xie,2019) approaches can identify one from another. According to research, the traits can be seen in both the temporal and spectral domains. Insects' temporal characteristics were discovered in soil and wood. It was determined to consist of subgroups of trains separated by less than 250 milliseconds and contained between 6 and 200 impulses. To distinguish between legitimate sound in seconds of time and unrequired noise, which often reaches peak energy at a seconds at a time in 10 seconds. These efforts have mostly concentrated on differentiating between flying and non-flying species. Signal Processing and advanced spectrum analysis techniques were used to explore a wider range of MFCC features. Stored product insects were detectea second.pectrum analysis. The singing insects were monitored automatically by sound parameterization technique using Linear Frequency Cepstral Coefficients (LFCCs). The insect sounds were identified using the Mel-frequency Cepstral Coefficient (MFCCs), But feature extraction is the initial stage in automatic MFCC insect detection. An algorithm or classifier should be used to distinguish the MFCC features from one another. In this area, the use of machine learning techniques is most suitable. The input samples have a direct impact on the computational complexity and detection performance of these techniques.

SOUND EFFECTS OF INSECTS			
NAME	INSECT TYPE	DURATION(Seconds)	TOTAL DURATION
Butterfly	Flyying	7	48.5
	Flying	10.5	
	Flying	10	
	Flying	10	
	Flying	11	
Cicada	Flying	11	48.7
	Flying	10.2	
	Flying	6	
	Flying	10.6	
	Flying	10.9	
Bees	Flying	10.8	53
	Flying	10.3	
	Flying	10.7	
	Flying	10.6	
	Flying	10.6	
Crickets	Flying	10.9	53.5
	Flying	10.8	
	Flying	10	
	Flying	10.9	
	Flying	10.9	
Mosquito	Flying	9	49
	Flying	10	
	Flying	10	
	Flying	10	
	Flying	10	
Grasshopper	Flying	10	51.9
	Flying	10	
	Flying	11	
	Flying	10	
	Flying	10.9	
Buggs	Flying	5	39.8
	Flying	10.8	
	Flying	11	
	Flying	10	
	Flying	3	
Termites	Non Flying	7	50.2
	Non Flying	10.9	
	Non Flying	10.6	
	Non Flying	10.8	
	Non Flying	10.9	
Beetles	Flying	7	14
	Flying	1	
	Flying	1	
	Flying	3	
	Flying	2	
Ant	Non Flying	10.8	51.6
	Non Flying	10.8	
	Non Flying	10	
	Non Flying	10	
	Non Flying	10	

Table1: Dataset of insects sounds

3 MFCC Feature Extraction for Recognition:

The system is investigated by features including widely used signal properties, and the cepstrum envelops feature set using Mel-frequency Cepstrum Coefficients (MFCCs).

3.1 The Cepstrum Coefficients of Mel-Frequency 2 (MFCCs) Functionality Set: . The fast Fourier Transform (FFT) spectrum does not reflect the human hearing perception, which concentrates on the low frequency for better recognition. The main steps are as follows:

3.1.1 Convert Linear Frequency to Mel Scales: The distance between those regions in the mel spectrogram is about the same. Similar to how we hear, this scaling makes it easier for humans to discern between similar low-frequency noises and similar high-frequency sounds. We will separate the audio signal into individual areas, or frames, and compute FFTs on each frame.

3.1.2 Calculate Mel Filter Banks: A triangle filter bank called Mel Filter Banks behaves similarly to whether the human ear detects sound, which is more discriminatory at shorter wavelengths and less discriminatory at longer wavelengths. Mel filter banks achieve this by giving better accuracy in the low-frequency range and less at high frequencies.

3.1.3 Discrete Cosine Transform: It analyzes sinusoids with amplitudes and frequency that can represent an image. Because it provides very strong energy compression, the Discrete Cosine Transform is used in lossless compression image compression.

3.2 Feature Extraction: There are endless ways the implementation:

3.2.1 Signal Pre-processing :

Naturally, insect sound vibrations are persistent. Automation is the early phase.

Analysis of the signal for efficient storage and other purposes. We assume that the analog to digital conversion procedure is finished.

digitally, then it is further processed. Preprocessing is used to generate consistent outcomes and features of various recording setups, such as microphones, and surroundings. Pre-processing involves standardization, framing, and pre-emphasis.

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3.2.2 Signal Segmentation :

Segmentation is the phenomenon of dividing the steps of the input samples into small time frames. The frame length must be chosen considering

small sampling frequencies

4 Analytical Solution :

4.1 Database :

We collected the database from the sound library on the mobcup (MobCup,2022), quick sounds (quick sounds,2022) ,pixabay (Pixabay ,2022)website. It includes 9 insects as Cicada, Bees , Crickets ,Mosquito ,Grasshopper ,Buggs,Termites ,Beetles , Ant.

4.2 Experimental Set-up:

These assesments were executed in Python and Scikit learn And we used the digital signal processing toolbox for extracting features, and the package for machine learning and data mining for classification of the Insects. There were two scenarios for classifying insect species, called species classification, and insect classification.
Before the two feature sets were fused together to form a bigger set each scenario's feature set (MFCC) was conducted individually . To perform classification and assess the accuracy of the feature sets, The Linear Discriminant (LD), Linear SVN. The accuracy of the feature sets were evaluated using Linear Discriminant (LD), Fine KNN(Ouattara,2019), Linear SVN.

The audio files were collected and divided into small sample audio frequencies and were grouped according to the type of insects, thus creating the dataset for the model.The model was trained with different Machine Learning Algorithms like KNN, SVM, SVC, Decision Tree etc.
Then, an MFCC feature vector was produced with 13 MFCC features and 5 low-level features that were retrieved from each signal segment. The response element is mostly used to create a row vector for training reasons in order to identify the class to whereby the signal belongs. The data set was randomly divided into 80% for training and 20% for Testing.

4.3 Species Classification :

Three feature sets were used for the classification: the MFCC set, and the combination of and MFCC set. Overall, the MFCC features provides better classification than the low-level feature set, except for the Fine K-Nearest Neignbor(KNN) with 85.4% accuracy. As a corollary, it can be concluded that the MFCC feature set indeed performs marvelously when used to extract signals from insect actions like migration and feed. Furthermore, the combined feature set (MFCC) improved the accuracy significantly.

Methods	Accuracy
1. KNN	85.4%
2. SVM	84.60%
3. SvC	84.20%

4. Tree	84 0%
5. Linear SVM	84.00%
6. Cosine KNN	83.90%
7.Medium KNN	83.80%

Table 2. Results obtained from the Classification

Conclusion:

There was a large challenge for the gathering of species of Butterfly, Bees, Bugs, Cicada, Cricket, Termites, Ant, Grasshopper, Mosquito, 9 different species and this study incorporates these nine insects' sounds with their MFCC(Mel-frequency cepstral coefficient) feature which create an extensive data set for evaluation different types of the sound of insects. This study also tested the features in different artificial intelligence-based models like this and out-of-source models, it has proven the features are useful for classification and training. Additionally, this research showed a very high accuracy of 85.4% from the k-nearest neighbor method. In the future, this study will extend its dataset by gathering more sounds from different sources and it will be implemented in remote monitoring projects to evaluate real-world sounds from different sources.

References

Chen, Y., Why, A., Batista, G., Mafra-Neto, A., & Keogh, E. (2014). Flying insect detection and classification with inexpensive sensors. *JoVE (Journal of Visualized Experiments)*, (92), e52111.

Lima, M. C. F., de Almeida Leandro, M. E. D., Valero, C., Coronel, L. C. P., & Bazzo, C. O. G. (2020). Automatic detection and monitoring of insect pests—a review. *Agriculture*, *10*(5), 161./

MobCup. (n.d.). Retrieved July 20, 2022, from https://mobcup.net/browse/ringtones/

Ouattara, Y. B., Kobea, T. A., Baudoin, G., & Laheurte, J. M. (2019). KNN and SVM Classification for Chainsaw Identification in the Forest Areas. *International journal of advanced computer science and applications (IJACSA)*, *10*(12).

Pixabay (n.d.). Retrieved July 20, 2022, from https:// pixabay.com/

Phung, Q. V., Ahmad, I., Habibi, D., & Hinckley, S. (2017). Automated insect detection using MFCC features based on sound generated from insect activities. *MFCCs Australia*, *45*(2), 445-451.

Quick sounds(n.d.). Retrieved July 20, 2022, from https://quicksounds.com/

Xie, J., & Bertram, S. M. (2019, December). Using machine learning techniques to classify cricket sound. In *Eleventh International Conference on Signal Processing Systems* (Vol. 11384, pp. 141-148). SPIE.