Flying Insect Identification Based on Wing-beat Frequency using Modified SVM Classifier

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ABSTRACT *This paper aims in recognizing insects based on their flight sound, using feature optimization technique. Entomologist nowadays have a great challenge in identifying the insects with good accuracy using an economical tool. Flight sound of insects is characterized by many features, especially by spectral and temporal features. With the selection of correct features and by using appropriate classifier, it is believed that high accuracy of recognition is possible.This paper mainly focusses on developing a complete digitized tool that includes process of detecting and monitoring insect species that threaten biological resources, in both productive and native ecosystems, particularly for pest management and biosecurity. It uses Tukey's methodto optimize the feature selection andmodifies Support Vector Machine (SVM) classifier in order to detect the insects. This work is implemented on the Benchmark dataset, ESC-50 and the recognition accuracy is 86.7%.*

***Keywords**: Feature Optimization; Tukey's method; Support Vector Machine classifier;ESC-50 database.*

I. INTRODUCTION

Our lifestyle and ecosystem are directly or indirectly associated with insects. This association results in both beneficial and unfavorable response to human life. Hence, Entomologists refer the relationship between human and insects as love-hate relationship. The unfavorable response from the insects cause diseases and thereby increasing the mortality rate. There are even some endangered species of insects that cause damages to the food crops and thereby producing a negative impact on the economic status of our Nation. Entomologists are aiming at reducing the effect of such unwanted species. Since certain species are secretive, sensitive to disturbance, it is not easy to observe and catch. Meanwhile, there exist beneficial insects that help in pollination of the food crops. Presently, a lot of open issues are there with the impact of insects on ecosystem that needs immediate attention.

A lot of novel and relevant applications have emerged with the development of tools and techniques of data mining methods for identification of insects. There exists a sensor that uses a laser and machine learning techniques to classify species of insects.This sensor is being considered as an important step in the development of intelligent traps. Such traps can attract and selectively capture insect species of interest, releasing all other species back into the environment. Then the unwanted insects are tracked and killed by the traps. But this kind of hardware traps are not affordable and usable in all circumstances.

For most applications in smart sensors, there is not an assumption that the data is generated by a stationary stochastic process. Hence, to manipulate such data is found to be too hard.

Subsequently, there is a need for a software tool that manipulates the temporal data associated with insects for the process of identification of insects. Hence, algorithms that classify such data streams often assume that once a prediction is made, the actual labels are provided with some delay to assist in updating the classifier. In the case of smart sensors, these labels are rarely available, and the application must adapt to concept drift without assuming that labels from test cases are known.

Human beings can easily classify audio signals all the time without any technical support. Human beings do not find it difficult to classify and recognize the voice over the telephone. But the same is considered to be a difficult process when the sound is weak or there is noise or if there are more sequence of similar sounds.

In order to recognize the acoustical features (Daniele Barchiesi, DimitriosGiannoulis, Dan Stowell and Mark D. Plumbley, 2015), there are three main areas that need to be focused in order to design an automated tool. First, it is necessary to understand how humans listen and recognize the sounds using their auditory behavior. This tends to have more research in psychological and

physiological than in computational area. Second, the research area focuses on how the machine could be trained to behave as a human in listening aids. Hence, the machine needs to be designed and programmed in such a way that it listens similar to human beings. Finally, the automated tool is developed in such a way that it can hear sound much better than a human. It needs to include modules for perceiving sound in the same way as that of microphone, noise removal, feature extraction and thereby to recognize the sound correctly with good accuracy.

II. Related Work

Several reviews focused on the classification algorithms that are used to recognize certain species based on the features extracted from the sounds made by them. This review also emphasizes its attention towards classification algorithms that segregates the dataset based on the same feature set extracted from sounds produced by the species. The feature set extracted need to be preprocessed and hence the review also adds some references for preprocessing techniques used related to acoustical sound domain.

The classifier (Hongtao Zhang, Yuxia Hu, 2010) is one of the important parts of the online detection system of the stored-grain insects based on the image recognition technology. By evaluating the correlation degree using mean and variance (Hongmei Zhang, QuangongHuo, Wei Ding, 2008) of the image features, the species of insects are identified. Standard area, perimeter, elongation, complexity, duty ratio, equivalent radius, roundness, second invariant moment and forth invariant moment are the features used for the classification process.

Region of Interest is being segmented from the images of live recorded insects and then a hybrid approach (Siti N. A. Hassan, Nadiah S. A. Rahman, ZawZawHtike and Shoon Lei Win, 2014) of color histogram, Gray Level Co-occurrence Matrix (GLCM) and pattern matching is used for insect recognition. Pattern matching is performed by correlating the feature vectors with certain threshold. Colour, texture and edges features are used for pattern matching.

Detection of pests using Bayesian classifier (AkritiParida, Sonal Kothari, NandhiniVineeth, 2015) on static and dynamic images. It involves series of preprocessing steps like obtaining a gray scale image of the original RGB image, segmentation of the image to enhance the desired object and to mask the background. Noise removal and extraction of important features like color, size and boundary are also done.

Classification based on Artificial Neural Networks (Samanta and Indrajit Ghosh, 2012) used eleven features (site-of-damage, leaf-surface, leaf-appearance, leaf-color, leaf-spot, mid-ribcolor, edge-color, tip-color, vein-color, finger-tip-test, bush-appearance) to identify the tea pests (Aphid, Helopeltis, Jussid, Pink Mite, Purple Mite, Red Spider, Scarlet Mite, Thrips) in tea gardens of North-Bengal districts of India. Correlation-based feature subset selection (CFS) (Luqman R. Bachtiar, Charles P. Unsworth, 2014) is used to speed up the classification process by reducing the dimensionality of the exact feature set. The classification accuracy is 100%. But this framework does not work for any other insect recognition.

Multivariate Time Series Classification Using Dynamic Time Warping Template Selection (Skyler Seto, Wenyu Zhang, Yichen Zhou, 2015) is used for Human Activity Recognition. It used a template selection approach instead of feature extraction and estimated time series similarity measure. The implementation of this method needs an increased computational cost.

Bayesian Classification of Flight Calls with a novel Dynamic Time Warping Kernel (TheodorosDamoulas, Samuel Henry, Andrew Farnsworth, 2010) used a Probabilistic Learning for classification with temporal features. And in order to improve the classification accuracy spatio-temporal information had to be integrated into the model.

Neural Network based insect classification in cotton ecosystems (Habib Gassoumi, Nadipuram R. Prasad, John J. Ellington, 2000) uses Structural features (relative location, relative area, edges, and curve) to classify insects as desirable and non-desirable insects.

Insect classification based on neural network using image features (Jeffrey Glick, Katarina Miller, 2016) uses the VGG-16 architecture. It fixes convolution layers with learning rate as 0 and trains forward layers. This architecture works for ImageNet images exploiting the feature extraction capabilities of the rear layers without spending computing time on re-training but focusses on fully connected layers. It achieves good accuracy on insect classification with a minimal amount of training.

Detection and Classification of Insect Sounds in a Grain Silo using a Neural Network (Kevin M. Coggins and Jose Principe, 2005) with feature extraction was trained to distinguish larvae, adult and false sounds. This system is implemented with grain-storage container, data acquisition system, and the neural network. The infected-larvae will be in positions equidistant to two piezoelectric

sensors while the adult insects freely roam the grain and they are active making sounds freely. And this paves a way for easy classification.

Insect sound is recognized using the spectral feature, Mel frequency cepstrum coefficient and probabilistic neural network (ZHU Le-Qing, 2011). This classification framework shows good performance in recognizing 50 specific sounds of insects.

Classification using Hidden Markov Model (Sarika Hegde, K. K. Achary and Surendra Shetty, 2015) with features extracted from Mel frequency cepstral coefficient is used for automatic speech recognition. This paper presents an efficient classification based on selected feature set. Fisher ratio technique evaluates the selection of feature set.

Classifiers based on Linear Discriminant Analysis (LDA) and decision trees (Kris West, Stephen Cox, 2004) using Spectral Contrast Feature and temporal variant features are used for musical audio signal classification (Tao Li.G. Tzanetakis, 2003) and achieves effective classification.

Support Vector Machine (Lie Lu, Hong-Jiang Zhang, Stan Z. Li, 2003) based classification on audio signals for identifying music, silence, background sound, pure speech, and non pure speech. Mel-frequency cepstral coefficients (MFCC) are computed using Fast Fourier Transformation. Temporal features like short time energy and zero crossing rate and Spectral features like spectral flux and spectral centroid are the statistical features considered for classification.

III.Data and Methods

A. *Dataset – ESC-50 (Environmental Sound Classification)*

The ESC-50 dataset contains 2000environmental audio recordings that are already labeled and can be used for acoustical sound classification. This dataset is available in a unified format (5-second-long clips, 44.1 kHz, single channel, OggVorbis compressed @ 192 kbit/s)with a collection of short environmental recordings.

At the time of testing from the Benchmark dataset, ESC-50, 200 files are considered in a cycle. Among which 100 are tested for insects and 150 for non-insects. And for the next cycle, remaining 200 files those which are not previously used are selected from the testing samples (80 + 100). The same process is repeated till all the 2000 files are used for the recognition of insects| non-insects. Table 3.1 shows the distribution of dataset as training and testing data.

Table 3.1 Distribution of dataset for classification

Dataset	ESC – 50		
	Insects	Non-insects	Total
Training Files	100	100	200
Testing Files	80	100	180

The entire work in this paper is depicted in Figure3.1. The proposed work accepts the wing beat frequency of insects. The input frequency is highly spectral, temporal and multi-dimensional. Feature setis extracted using Fast Fourier Transformation. The analysis of extracted features shows that the data are time variant with many hidden patterns; hence the data need to have anoptimal representation. For such optimal representation, outliers from the feature set are removed by outlier omitting method, Tukey's method. Available data is divided as training and testing purpose. The SVMclassifier is modified with the inclusion of Tukey's method to improve the speed and accuracy of classification.

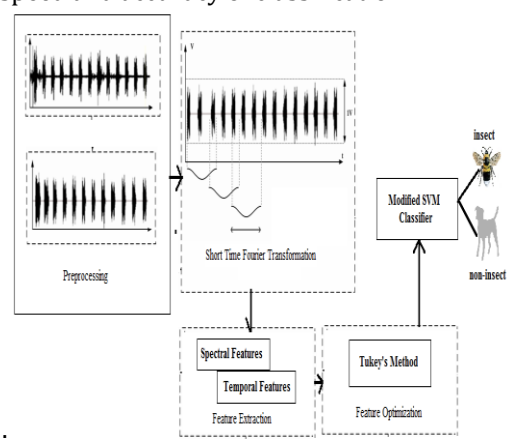

Figure 3.1 Overall block diagram of the proposed work

Preprocessing

The input wing beat frequencies are hyperspectral, multi-dimensional, time-variant, with missing patterns, partially incomplete, and highly dynamic in nature. Hence, for further processing of such acoustical features, the entire dataset need to be optimized. The dominant frequency of the insects is 2-13 kHz. Since the signal was recorded in the natural environment,all sounds were disturbed by some sources near each observation such as the wind, truck sounds, and animal sounds. On account of the fact that this type of evidence is concentrated in the frequencies upper 2.S kHz, it can be removed with a high-pass filter. Dynamic Time Warping optimally aligns two time series sequences and captures similarities among both the sequences.

B. ***Short Time Fourier Transformation (STFT)***

Short Time Fourier Transformation divides a longer time signal into shorter segments of equal length and determines the sinusoidal frequency and phase content of local sections of a signal as it changes over time.

C. ***Feature Extraction***

Discrete Fourier Transform (DFT) is used as feature-extraction technique in this work that transforms the time-series data into the frequency domain, where data dimensionality can be reduced and frequency components can be extracted. In case of existence of noise in the sequence, Fourier transformation does not perform well and then short time Fourier transformation is used as it can extract both time and frequency domain information. All audio features are extracted from the successive windows or frames of the audio sequence. The spectral decomposition of the signal is represented by finite number of sine/cosine waves. Each wave is the Fourier coefficient and is with low amplitude. These low amplitude coefficients are discarded without loss of information. The features that are considered in this research work include the temporal features like zero crossing rate and short time energy and spectral features like spectral flux, spectral centroid, spectral roll off, spectral flatness, and spectral bandwidth that discriminates the features in identifying the insects.

(i) Spectral Flux

Spectral flux is computed as a measure of the degree of variation in the spectrum across time and this is restricted to the positive changes. It is summed across all frequency bins, and defmed as,

$$SFL(m) = \sum_{k=-\frac{Nf}{2}}^{\frac{Nf}{2}-1} W(|\,X(m.k)| - |X(m-1,k)|)$$

where SFL is the spectral flux and W(X) is the half wave rectifier function.

(ii) Spectral Centroid

Spectral centroid is used to characterize the spectrum. The individual centroid of a spectral frame is computed as the average frequency weighted by amplitudes, divided by the sum of the amplitudes. The spectral centroid is used to compute the center value of the groups for each insect frequency band.

$$SC = \sum_{f\,=1}^{Nf} f\ \frac{X[f]}{\sum_{f=1}^{Nf} X[f]}$$

where the SC denotes the spectral centroid, f is the frequency domain, X[f] represents the normalized amplitude in the spectral domain and N_f is the maximum frequency of each insect signal. The spectral centroid is usually considerably higher than one. And this contributes to the average.

(iii) Spectral Roll off

The spectral roll-off point is correlated to the harmonic cutting frequency.

$$\sum_{f=0}^{Fsr} X^2\,[f] = 0.85 \sum_{f=0}^{Fs} X^2\,[f]$$

where F_{SR} is the spectral roll-off point, F_s the Nyquist frequency

(iv) Spectral Flatness

The flatness of spectrum is the feature that is used in acoustical sound analysis. The spectral flatness IS a measure of the noisiness of a spectrum.

$$SF = \frac{\exp\left(\frac{1}{2\pi}\sum_{w=-\pi}^{\pi} 1nX[w]\right)}{\frac{1}{2\pi\sum_{w=-\pi}^{\pi} 1nX[w]}}$$

where X [w] is the spectral of the signal.

D. ***Feature Optimization***

In this paper, the feature set is optimized by deleting the outliers. Tukey's method of removing outliers is applied that uses the following formula.

$(k+1)Q_1 + k\,Q_3 > X_i > (k+1)Q_3 + k\,Q_1$

where k is the outlier coefficient (assumed to be 1.5) and Q_1 and Q_3 are the 25th and 75th percentile of each of the feature (X_i).

E. ***Modified SVM Classifier***

The pseudo code of modified SVM classifier is depicted below:.

1. Accept the insect sound
2. Preprocess the accepted data using DTW
3. Align the dataset using STFT
4. Optimize the data using Tukey's method
5. Select the hyperplane to segregate the feature set
6. Generate two parallel hyperplanes
7. Find the distance between feature set and hyperplanes
8. Classify the data according to the calculated distances

IV. Experimental Evaluation and Results

This work extracted spectral and temporal features of the acoustical sound of insects from the ESC-50 dataset. The files of entire database is categorized as training, testing and validation sets in each class and are shown in Table 4.1. The files are used for training, testing and validation in the ratio of 50:25:25 percentage from the dataset. Table 4.2 shows the distance measures of the feature vectors. Table 4.3 shows the results of classification on ESC-50 dataset. Table 4.4 shows

the accuracy produced.

Table 4.1 Training and testing files of ESC-50 dataset

Dataset	ESC – 50		
FileTypes	Insects	Non-insects	Total
Training Files	100	100	200
Testing Files	80	100	180
Validating Files	80	100	180

Figure 4.1 depicts how the feature values of Spectral Centroid is being used for the identification of insects using modified SVM Classifier.

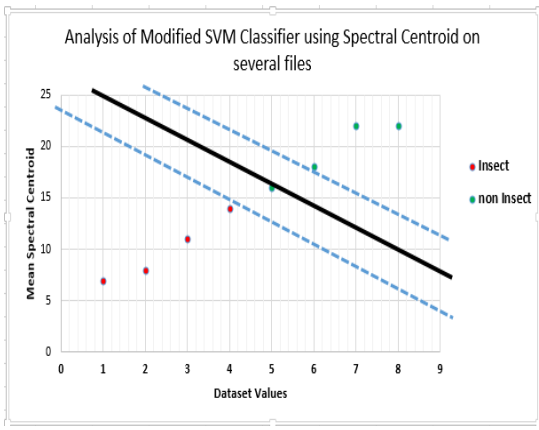

Figure 4.1 Spectral Centroid value over modified SVM Classifier

The confusion matrix for the evaluation of accuracy of classification of insect | non-insect on ESC-50 dataset using modified SVM is shown in Table 4.4 and Table 4.5 gives the accuracy of classification using ordinary SVM classifier.

Table 4.4 Accuracy recorded using modified SVM classifier on ESC-50. The above confusion matrices show that the accuracy in identifying insects on ESC-50 dataset with modified SVM Classifier is 11.21% greater than that of classification using SVM classifier.The analysis is shown in figure 4.2.

V. CONCLUSION

A framework has been developed to identify insect | non-insect using modified Support Vector Machine classifier. The accuracy in recognition of the species based on its sound as insect or non-insect is improved while using modified SVM classifier. The modified SVM classifier, in the sense it had used the Tukey's method of optimizing the feature vector. This method reduces the computational complexity of feature vector utilization in the process of classification. Modified SVM classifier again it has used best suited kernel and parameters for classification of the acoustical sound. The analysis is performed using distance measure between the training data and the hyper-plane of an SVM classifier. It uses the statistical measures in order to generate the hyper-plane and thereby to identify the support vectors or marginal points to better classify the points into either insect class or non-insect class with the accuracy of 86.70%. This classification accuracy is 11.21% greater than ordinary SVM classifier.

Table 4.2Distance Measure and Support Vectors for ESC-50 dataset

Training dataset	25 Files	
Margin	0.27852	
Sample Nos.	Distance	Support Vector
1	0.358	Y
2	0.312	
3	0.284	
4	0.299	
5	0.115	Y
6	0.320	Y
7	0.345	Y
8	0.542	
9	0.784	
10	0.250	Y
11	0.305	Y
12	0.296	
13	0.151	Y
14	0.354	
15	0.261	Y

Table 4.3 Results of Classification algorithms on ESC-50

Clustering Algorithm	Test Files (ESC-50)	Sample Test Filename	Insect | Non-Insect
SVM	https://github.com/karoldvl/ESC-m50 Tested 300 files (150 insects and 150 non-insects) out of 2000 files	1-73585-A.ogg	Insect

	Insect	Non Insect	Total
Class 1 (Insect)	93	12	105
Class 2 (Non Insect)	16	83	99
Total	109	95	204
Accuracy	86.70		
Precision	88.57		
Recall	85.32		

Table 4.5 Confusion Matrix for SVM classifier on ESC-50

	Insect	Non Insect	Total
Class 1 (Insect)	71	34	**105**
Class 2 (Non Insect)	16	83	**99**
Total	**87**	**117**	**204**
Accuracy	**75.49**		
Precision	**75.72**		
Recall	**76.28**		

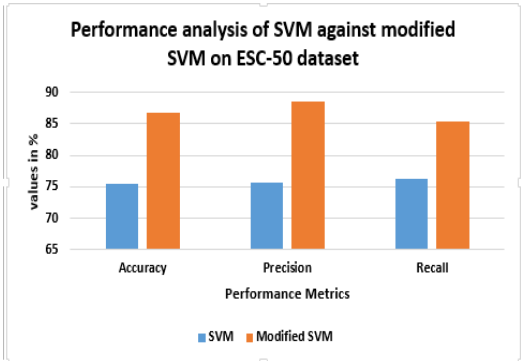

Figure 4.2 Performance analysis of SVM against modified SVM

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