

# Automatic Classification of Multiple Acoustic Events Using Artificial Neural Networks

Dineth Egodage

188015M

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## DECLARATION

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## ABSTRACT

There are numerous scenarios where similar acoustic events occur multiple times. Acoustic monitoring of migratory birds is an ideal example. Birds make a type of call known as flight calls during migration. A flight call can be considered as *an acoustic event* because it is a short-term, intuitively distinct sound. It is challenging to identify multiple occurrences of extremely short-range acoustic events such as flight calls in real-world recordings using classification techniques that require more computational power. It is mainly due to background noise and complex acoustic environments. This research aims at developing a classification model that reduces the effect of background noise, extract ROIs from continuous recordings, extract suitable features of flight calls and detect multiple occurrences of flight calls. An improved algorithm that can extract features has been developed in this research—by combining a well known Maximally Stable Extremal Regions (MSER) technique with state of the art traditional techniques. Namely Spectral and Temporal Features(SATF) and a combination of SATF and Spectrogram-based Image Frequency Statistics(SIFS). We name this novel algorithm as Spectrogram-based Maximally Stable Extremal Regions (SMSER). Three distinct feature sets have formed such that Featureset-1 created using SATF. Featureset-2 is a blend of SATF and SIFS. Featureset-3 is a combination of SATF, SIFS, and SMSER. The kNN, RF, SVM, and DNN classification techniques evaluated a real-world dataset using the extracted feature sets. Research carried out several tests to find out the best performing combination of classification model and feature set. The results showed that the flight calls' detection accuracy increased when the number of features increased, although high computational power requirement is a disadvantage. The performance of SMSER feature set was the best among almost every classification technique above. It should be because the SMSER Feature set has the highest number of features. Classification of the SMSER feature set from the DNN classifier showed the highest accuracy of 87.67%.

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## LIST OF ABBREVIATIONS

ANN	Artificial Neural Networks
DNN	Deep Neural Network
DFT	Discrete Fourier Transformation
DWTC	Discrete Wavelet Transform Coefficients
FFT	Fast Fourier Transformation
GMM	Gaussian Mixture Models
GPU	Graphics Processing Unit
HMM	Hidden Markov Models
k-NN	k-Nearest Neighbor
MFCC	Mel Frequency Cepstral Coefficients
PC	Personal Computer
PCA	Principal Component Analysis
RF	Random Forest Algorithm
RFE	Recursive Feature Elimination
RMSE	Root Mean Square Energy
SATF	Spectral and Temporal Features
SIFS	Spectrogram-based Image Frequency Statistics
SMSEER	Spectrogram-based Maximally Stable Extremal Regions
SVM	Support Vector Machine
ZCR	Zero-Crossing Rate



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