

SWIFTLET SOUND IDENTIFICATION USING  
VECTOR QUANTIZATION AND GAUSSIAN  
MIXTURE MODEL

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## **SUPERVISOR'S DECLARATION**

We hereby declare that we have checked this thesis and in our opinion, this thesis is adequate in terms of scope and quality for the award of the degree of Master of Engineering (Electronic).

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## **STUDENT'S DECLARATION**

I hereby declare that the work in this thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at Universiti Malaysia Pahang or any other institutions.

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## TABLE OF CONTENT

<b>DECLARATION</b>	
<b>TITLE PAGE</b>	
<b>ACKNOWLEDGEMENTS</b>	<b>ii</b>
<b>ABSTRAK</b>	<b>iii</b>
<b>ABSTRACT</b>	<b>iv</b>
<b>TABLE OF CONTENT</b>	<b>v</b>
<b>LIST OF TABLES</b>	<b>viii</b>
<b>LIST OF FIGURES</b>	<b>ix</b>
<b>LIST OF SYMBOLS</b>	<b>xi</b>
<b>LIST OF ABBREVIATIONS</b>	<b>xii</b>
<b>CHAPTER 1 INTRODUCTION</b>	<b>1</b>
1.1 Background of Study	1
1.2 Problem Statement	2
1.3 Research Objectives	3
1.4 Scope of research	3
1.5 Thesis contribution	4
1.6 Thesis Overview	5
<b>CHAPTER 2 LITERATURE REVIEW</b>	<b>6</b>
2.1 Introduction	6
2.2 Swiftlet	6
2.2.1 Swiftlet Attraction Using Sound	8

2.3	Feature Extraction for Animal Sound	10
2.4	Classification for Animal Sound	11
2.4.1	Minimum Distance Classifier (MDC)	13
2.4.2	Vector Quantization (VQ)	15
2.4.3	Gaussian Mixture Model (GMM)	17
2.5	Data Corpora	18
2.6	Chapter Summary	19
 <b>CHAPTER 3 METHODOLOGY</b>		<b>21</b>
3.1	Introduction	21
3.2	Methodology	21
3.3	Feature Extraction	23
3.3.1	Mel Frequency Cepstral Coefficient (MFCC)	24
3.3.2	Linear Prediction Cepstral Coefficient (LPCC)	29
3.4	Alternative Techniques	33
3.4.1	Minimum Distance Classifier (MDC)	34
3.5	Propose models	34
3.5.1	Vector Quantization (VQ)	35
3.5.2	Gaussian Mixture Model (GMM)	36
3.6	Chapter Summary	38
 <b>CHAPTER 4 RESULTS AND DISCUSSION</b>		<b>39</b>
4.1	Introduction	39
4.2	Data Collection	39
4.3	Experiment Setup	42
4.4	Result and Discussion	43

4.4.1	Result using Minimum Distance Classifier (MDC)	44
4.4.2	Result using Vector Quantization (VQ)	47
4.4.3	Result using Gaussian Mixture Model (GMM)	53
4.4.4	Comparison the best performance of VQ and GMM with MDC	58
4.4.5	Feature Improvement by Dynamic Feature Impact	61
4.5	Chapter Summary	64
<b>CHAPTER 5 CONCLUSION</b>		<b>66</b>
5.1	Introduction	66
5.2	Conclusion	66
5.3	Future Work	67
<b>REFERENCES</b>		<b>69</b>
<b>APPENDIX A RESULT OF CONFUSION MATRIX</b>		<b>75</b>
<b>APPENDIX B LIST OF PUBLICATIONS</b>		<b>78</b>



## LIST OF TABLES

Table 4.1	Total samples of swiftlet sound	40
Table 4.2	Confusion matrix using MDC with LPCC features	44
Table 4.3	Confusion matrix using MDC with MFCC features	44
Table 4.4	Confusion matrix using VQ (8-codebook) with LPCC features	47
Table 4.5	Confusion matrix using VQ (8-codebook) with MFCC features	47
Table 4.6	Confusion matrix using VQ (16-codebook) with LPCC features	48
Table 4.7	Confusion matrix using VQ (16-codebook) with MFCC features	48
Table 4.8	Confusion matrix using VQ (32-codebook) with LPCC features	49
Table 4.9	Confusion matrix using VQ (32-codebook) with MFCC features	49
Table 4.10	Confusion matrix using VQ (64-codebook) with LPCC features	50
Table 4.11	Confusion matrix using VQ (64-codebook) with MFCC features	50
Table 4.12	Confusion matrix using GMM (1-mixture) with LPCC features	54
Table 4.13	Confusion matrix using GMM (1-mixture) with MFCC features	54
Table 4.14	Confusion matrix using GMM (2-mixture) with LPCC features	55
Table 4.15	Confusion matrix using GMM (2-mixture) with MFCC features	55
Table A.1	Confusion matrix using MDC with LPCC_D and LPCC_DA	75
Table A.2	Confusion matrix using MDC with MFCC_D and MFCC_DA	75
Table A.3	Confusion matrix using VQ (64-codebook) with LPCC_D	75
Table A.4	Confusion matrix using VQ (64-codebook) with LPCC_DA	76
Table A.5	Confusion matrix using VQ (64-codebook) with MFCC_D	76
Table A.6	Confusion matrix using VQ (64-codebook) with MFCC_DA	76
Table A.7	Confusion matrix using GMM (2-mixture) with LPCC_D	76
Table A.8	Confusion matrix using GMM (2-mixture) with LPCC_DA	77
Table A.9	Confusion matrix using GMM (2-mixture) with MFCC_D	77
Table A.10	Confusion matrix using GMM (2-mixture) with MFCC_DA	77

## LIST OF FIGURES

Figure 2.1	White-nest Swiftlets ( <i>Aerodramus fuciphagus</i> )	7
Figure 2.2	Black-nest Swiftlets ( <i>Aerodramus Maximus</i> )	8
Figure 2.3	Concept of Minimum Distance Classifier	14
Figure 2.4	Codewords in 2-dimensional space.	16
Figure 3.1	Basic step of speaker processing	21
Figure 3.2	Research Methodology	22
Figure 3.3	Mel frequency warping function	24
Figure 3.4	An example of mel frequency filterbank	25
Figure 3.5	Block diagram of the computation steps of MFCC	25
Figure 3.6	Block diagram of the computation steps of LPCC	31
Figure 3.7	Minimum Distance Classifier Model	34
Figure 3.8	Vector Quantization Model	36
Figure 3.9	Gaussian Mixture Model	37
Figure 4.1	Baby Spectrogram	40
Figure 4.2	Adult Spectrogram	41
Figure 4.3	Colony Spectrogram	41
Figure 4.4	A block diagram of training and testing swiftlet sound identification	42
Figure 4.5	The performance of the system using MDC as classifier with two different feature extraction method, LPCC, and MFCC	45
Figure 4.6	The performance of the system using MDC as classifier with two different feature extraction method, LPCC, and MFCC	46
Figure 4.7	The performance of total accuracy using VQ with 8, 16, 32 and 64 codebook	51
Figure 4.8	The performance of the system with different size of VQ codebook size using two types of feature extraction technique, LPCC, and MFCC	52
Figure 4.9	The performance GMM with 1-mixture and 2-mixture with LPCC and MFCC	56
Figure 4.10	The performance of the system with different number of mixtures of GMM using two types of feature extraction technique, LPCC, and MFCC	57
Figure 4.11	The performance using MDC, VQ (64-codebook) and GMM (2-mixture)	58
Figure 4.12	Details accuracy for each sound for MDC, VQ (64-codebook) and GMM (2- mixture)	60
Figure 4.13	Dynamic Features Impact Performance	62

Figure 4.14	Comparison GMM by 2-mixture with additional Delta-Acceleration (_DA) features qualifier and Original (_0)	63
Figure 4.15	Summary of chapter 4	65

## LIST OF SYMBOLS

$f$	Frequency
$f_s$	Sampling frequency
$H_{km}$	Mel filter bank
$H_z$	Transfer function
$M$	Overlap window size
$M_f$	Number of filter bank
$N$	Window size
$P$	Magnitude Spectrum
$S$	Audio signal

## LIST OF ABBREVIATIONS

CD	Compact Disk
D	Delta
DA	Delta-Acceleration
DCT	Discrete Cosine Transform
DTW	Dynamic Time Wrapping
EM	Expectation-Maximization
FFT	Fast Fourier Transform
GMM	Gaussian Mixture Model
HMM	Hidden Markov Model
LDA	Linear Discriminant Analysis
LPC	Linear Predictive Coding
LPCC	Linear Predictive Cepstral Coefficient
MDC	Minimum Distance Classifier
MDC	Minimum Distance Classifier
MFCC	Mel Frequency Cepstral Coefficient
SVM	Support Vector Machine
VQ	Vector Quantization
VQLBG	Vector Quantization Linde-Buzo and Gray

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## ABSTRAK

Pengesanan bunyi burung merupakan salah satu aplikasi dalam teknologi mengesanan audio. Pengesanan bunyi ini adalah cara terbaik untuk mengenalpasti jenis bunyi burung walet yang berlainan antara bunyi anak, dewasa dan berkumpulan. Realitinya, pengkaji burung sukar untuk membezakan ketiga-tiga jenis bunyi ini secara kasar kecuali dengan bantuan orang yang berpengalaman dalam bidang perindustrian burung walet. Pengesanan bunyi burung walet berguna dalam perindustrian burung walet dalam meningkatkan penghasilan sarang burung dan kualiti habitat disebabkan kehidupan burung walet tertarik kepada bunyi. Tujuan kajian ini akan mengaplikasikan cara untuk mengklasifikasi tiga jenis burung walet ini menggunakan teknologi pengesanan audio. Secara ringkasnya, kajian ini akan mengekstrak ciri-ciri audio bunyi burung walet menggunakan Linear Predictive Cepstral Coefficient (LPCC), dan Mel Frequency Cepstral Coefficient (MFCC) seterusnya mengklasifikasikan menggunakan teknik Minimum Distance Classifier (MDC), Vector Quantization (VQ) and Gaussian Mixture Model (GMM). Langkah pertama, ciri-ciri audio diekstrak menggunakan LPCC dan MFCC dan disimpan di dalam data simpanan. Langkah kedua, data simpanan tadi akan digunakan ketika teknik pengklasifikasi menggunakan teknik MDC, VQ bersama saiz kod buku 8, 16, 32 dan 64 serta teknik GMM bersama 1-campuran dan 2-campuran. Langkah ketiga, keputusan yang terbaik dipilih untuk penambahan ciri seperti Delta dan Delta-Acceleration untuk tujuan penambahbaikan peratus kejituan untuk hasil keputusan yang lebih baik. Keputusan yang diperolehi dalam kajian ini, ciri-ciri pengestrakan menggunakan MFCC bersama teknik klasifikasi GMM 2-campuran memberi keputusan 88.89% kejituan pengesanan bunyi burung walet yang tepat. Di akhir keputusan eksperimen mendapati, peningkatan 6.67% kejituan apabila menambah ciri ekstrak Delta-Acceleration sehingga mencapai 95.56% kejituan pengesanan bunyi burung yang boleh dikira peratus yang sangat baik. Kesimpulannya, cara untuk mengesanan bunyi burung walet dalam sistem ini melalui ciri pengestrakan menggunakan MFCC dengan ciri ekstrak tambahan Delta-Acceleration dan di klasifikasi melalui teknik GMM 2-campuran.

## ABSTRACT

Bird sound identification has become one of the applications in audio recognition technology. Audio recognition is a great way to classify swiftlet's sound between baby, adult, and colony. In real life, biologists are having difficulties to identify the difference between these three types of sound except for human expert hearing experience in swiftlet farming. The identification of swiftlet sound is used to increase the production nest and quality of habitat because the main characteristic of swiftlet is its attraction toward sound. The aim of this study is to implement in swiftlet sound specifically using audio recognition to identify the types of sound. In this work, swiftlet sound feature extracted using Linear Predictive Cepstral Coefficient (LPCC), and Mel Frequency Cepstral Coefficient (MFCC) then classify the sounds using Minimum Distance Classifier (MDC), Vector Quantization (VQ) and Gaussian Mixture Model (GMM). Firstly, the features extracted using LPCC and MFCC are stored in the database. Secondly, feature extraction results in the database used for classifying the swiftlets sound using MDC, VQ with codebook size is 8, 16, 32 and 64 and GMM by 1-mixture and 2-mixture for classification. Thirdly, the best performance classification selected for an additional feature in feature extraction such as Delta and Delta-Acceleration qualifier to improve accuracy for getting a better result. Based on the result of this study, the best performance was selected based on higher accuracy identification is MFCC with GMM by 2-mixture accuracy 88.89%. At the end of the experiment, the MFCC with additional features Delta-Acceleration using classification GMM by 2-mixture with improvement 6.67% compared to original and make it up to 95.56% accuracy which is considered as good percentage result. As conclusion, the best feature extraction for swiftlet sound identification is MFCC with Delta-Acceleration features by classify the sound using GMM 2-mixture.



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