



**Investigation of Robust Speech Feature Extraction
Techniques for Accents Classification of Malaysian
English Speakers**

by

**Yusnita Mohd Ali
(1040610467)**

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DECLARATION OF THESIS

Author's full name : YUSNITA BINTI MOHD ALI
Date of birth : 09 MARCH 1974
Title : INVESTIGATION OF ROBUST SPEECH FEATURES
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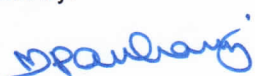
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Certified by:


SIGNATURE OF SUPERVISOR

DR. PAULRAJ M P
NAME OF SUPERVISOR

Date : 23/7/2014
DR. PAULRAJ M P
Professor
School of Mechatronic Engineering
University Malaysia Perlis
02600 Ulu Pauh, Perlis, Malaysia.
Email: paul@unimap.edu.my

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THESIS DECLARATION

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LIST OF ABBREVIATIONS

AAC	Automatic Accent Classification
AE	American English
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
ASR	Automatic Speech Recognition
BrE	British English
BruE	Brunei English
BS	Baseline
CALL	Computer-assisted Language Learning
CRD	Completely Randomized Design
CRs	Classification rates
dB	Decibels
DOE	Design of Experiments
DWT	Discrete Wavelet Transform
FF-MLP	Feed forward Multilayer Perceptron
FIR	Finite Impulse Response
FIS	Fuzzy Inference System
Formants	Formant frequencies
GMM	Gaussian Mixture Model
GSTs	Global Statistical Thresholds
HMM	Hidden Markov Model
Hz	Hertz
ICA	Independent Component Analysis
IWs	Isolated Words
KNN	K-nearest Neighbors
LDA	Linear Discriminant Analysis
LPC	Linear Prediction Coefficients
MalE	Malaysian English
MAP	Maximum-a-Posteriori
MBSE	Mel-band Spectral Energy
MFCC	Mel-frequency Cepstral Coefficients
MLLR	Maximum Likelihood Linear Regression

MMS	Maximum-mean subtraction normalization
mse	Mean-squared errors
msec	milliseconds
MVN	Mean and variance normalization
PCA	Principal Component Analysis
PD	Pronunciation Dictionary
PPRLM	Parallel Phone Recognition Language Modeling
PRLM	Phone Recognition Language Modeling
QMF	Quadrature Mirror Filters
RFE	Recursive Feature Elimination
RP	Received Pronunciation
SBS	Statistical Band Selection
SFFs	Spectral Feature Fusions
SgE	Singapore English
SNR	Signal-to-Noise Ratio
STE	Short-time Energy
STFT	Short-time Fourier Transform
STs	Sentences
SVM	Support Vector Machine
SVM-RFE	Support Vector Machine-Recursive Feature Elimination
TTS	Text-to-Speech
V-UV	Voiced-Unvoiced
ZCR	Zero-crossing Rate

LIST OF SYMBOLS

α	Learning rate of ANN
β	Momentum rate of ANN

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Kajian terhadap Teknik Penyarian Sifat Pertuturan Lasak untuk Pengelasan Loghat Bagi Penutur Bahasa Inggeris Berbangsa Malaysia

ABSTRAK

Sistem pengecaman pertuturan automatik (ASR) bukanlah suatu topik baru dalam pemprosesan pertuturan dan interaksi manusia-mesin. Ianya telah dikaji lebih daripada lima dekad lepas. Walau bagaimanapun, loghat kekal sebagai cabaran besar berkait rapat dengan kepelbagaian bahasa dalam isu-isu ASR masakini yang menggambarkan perbezaan pertuturan dalam sebutan dan intonasi seseorang yang mempunyai pelbagai perbezaan latar-belakang dari segi sosiolinguistik. Terdapat banyak dan pelbagai literatur yang telah mendedahkan kesan negatif daripada pelbagai loghat sebagai penyebab kemerosotan prestasi ASR. Walaupun loghat Bahasa Inggeris telah menjadi jenis loghat paling banyak dikaji kerana diangkat sebagai bahasa yang paling penting dan berprestij, Male yang merupakan versi baru didalam 'New Englishes' dikalangan penutur bukan ibunda masih belum diterokai. Dalam produk pasaran ASR pada masa kini, Male dianggap sebagai versi yang seragam secara konvensional walaupun tanggapan ini dipertikaikan oleh ramai sarjana dan penyelidik yang menganggap Male sebagai penuturan yang terhasil daripada implikasi setempat kepelbagaian etnik. Kajian persepsi yang lepas telah melaporkan kemungkinan tinggi mengesan identiti etnik daripada penuturan Singapore English (SgE) dan Brunei English (BruE) yang boleh dijadikan perbandingan yang sesuai dengan Male melalui ujian pendengaran. Pada masa ini, tiada kajian yang telah dilakukan untuk mengenal pasti asal usul etnik dari sampel penuturan Male menggunakan pelbagai teknik analisis pertuturan dan algoritma pembelajaran mesin untuk pengelasan automatik yang lebih dapat dipercayai, standard dan tepat melalui kaedah eksperimen. Kajian ini merupakan satu cubaan untuk mengisi jurang tersebut dan untuk tujuan ini, satu pangkalan data baru loghat Male telah dibina. Kajian ini merangsang sebutan jenis IWs dan STs daripada para pelajar universiti (lelaki dan perempuan) yang terdiri daripada tiga etnik utama di negara ini iaitu Melayu, Cina dan India yang mewakili para penutur berpendidikan tinggi menggunakan perkataan yang sensitif kepada loghat, dipilih daripada kajian yang lepas. Reka bentuk sistem yang dicadangkan terdiri daripada pra-pemprosesan, penyarian sifat dan pengelasan. Selain daripada pra-pemprosesan asas, kajian ini mencadangkan integrasi dengan sistem inferens kabur untuk segmentasi asas frem suara kepada bergetar-tidak bergetar (FIS V-UV) turut menyumbang kepada pelaksanaan sistem keseluruhan yang lebih baik berbanding sistem pengelasan loghat (AAC) konvensional. Satu kaedah baru yang dicadangkan yang dinamakan sebagai ambang statistik global (GSTs) untuk membina fungsi keahlian masukan-masukan tenaga pendek masa (STE) dan kadar lintasan sifar (ZCR) dalam segmentasi FIS V-UV telah mengurangkan jumlah frem yang perlu diproses di peringkat penyarian ciri. Keputusan eksperimen menunjukkan keberkesanan AAC-terbantu FIS V-UV yang dicadangkan menggunakan GSTs dengan peningkatan tertinggi dalam kadar ketepatan sebanyak 7.70% dan pengurangan frem sebanyak 24.26% berbanding AAC konvensional. Pada peringkat kedua, ciri-ciri akustik berkait rapat dengan loghat daripada tiga etnik dibangunkan melalui beberapa kaedah analisis bank-penuras, model saluran vokal, analisis hibrid dan analisis paduan. Daripada lapan vektor sifat yang diuji ke atas pangkalan data Male, perihalan statistik tenaga spektrum jalur-Mel (MBSE), analisis komponen utama-berubah MBSE (disingkatkan sebagai PCA-MBSE), dua teknik hibrid ombak kecil diskret berubah diperolehi pekali ramalan