



**A STUDY ON ARABIC PHONEMES TOWARDS AN
AUTOMATIC TEACHING SYSTEM FOR THE
RECITATION OF HOLY QUR'AN**

By

Fatma Shawky AbdEl-Hamid Mohamed Khaled

A Thesis Submitted to the
Faculty of Engineering at Cairo University
In Partial Fulfillment of the
Requirements for the Degree of
MASTER OF SCIENCE
In
Biomedical Engineering and Systems

**FACULTY OF ENGINEERING, CAIRO UNIVERSITY
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Title of Thesis:

A Study on Arabic Phoneme Towards an Automatic Teaching System for the
Recitation of Holy Qur'an.

Key Words:

Speech recognition; Hidden Markov Model (HMM); Mel Frequency Cepstral
Coefficients (MFCC); Classical Arabic (CA)

Summary:

This thesis is part of ongoing integrated studies concerning Classical Arabic recognition for both teaching and learning purposes. The major point of strength is using Al Norania Rule for the first time as training and testing dataset to differentiate between Arabic phonemes based on their exits and characteristics. This presents a substantial contribution summing up recognition models for recognizing different features and tiny details of each letter. This work is a good seed for different speech synthesis or speech recognition projects later on.

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Dedication

This work is dedicated to my family.

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List of Abbreviations

ASR	Automatic speech recognition
C	Consonant
CA	Classical Arabic
DFT	Discrete Fourier Transform
DCT	Discrete Cosine Transform
HMM	Hidden Markov Models
HTK	Hidden Markov Model Toolkit
IDFT	Inverse Discrete Fourier Transform
MSA	Modern Standard Arabic
MLF	Master Label Files
MFCC	Mel Frequency Cepstral Coefficients
NUMCEPS	Number of Cepstral Coefficients
V	Vowel

Abstract

This thesis investigates the sensitivity of MFCC features to recognize and differentiate fine differences between uttered Classical Arabic phonemes.

Correct pronunciation of Classical Arabic phonemes depends on their exits and characteristics. Al Norania rules were compromised to be used as a tool for teaching nonnative Arabic speakers the correct pronunciations of Classical Arabic phonemes.

A model was built based on MFCC features to investigate its sensitivity to different changes with respect to reference pronunciation

A speech corpus of syllables and phonemes was collected from audio signals of guaranteed readers of Al Norania rule. The majority of collected data was used as training data set; the remaining part was used as testing data set.

These syllables and phonemes were clustered according to their exits and characteristics. Then multiple features were extracted from each cluster using Mel Frequency Cepstral Coefficients (MFCC) -as the chosen feature extraction technique- examining different coefficients combinations and converting analogue form of speech signals into a parametric representation, from which parameters of Hidden Markov Models (HMM) were estimated for both training and testing processes.

Statistical results showed recognition accuracy of different models applied on the same cluster set. By comparing these results, it was found that the highest recognition accuracy for each cluster set was obtained using a specific MFCC recognition model, extracting features of very tiny details of this cluster.

Duration of pronunciation of tested phonemes was measured. Results showed different values according to belonging to one of three categories: explosive, in-between and softness phonemes (حروف شديدة. حروف توسط. حروف رخوة), keeping a constant ratio between median values of the three categories. To achieve correct pronunciation, this ratio should be kept for different persons and different methods of recitations for Holy Qur'an.

These findings can be summed up as a rigid frame for implementing an automatic system for both teaching and testing recitation of Holy Qur'an, and many educational projects preserving correct pronunciation of eloquent Arabic.

Chapter 1

Introduction

The Arabic Language serves as a powerful symbol of Arab national identity; ranks sixth in the world's league table of languages with an estimated 186 million native speakers. This language is considered one of the major languages of the world reflecting not only its number of speakers but also the important role that it played in history and is still playing especially in the development of Arab-Muslim Society [1-3].

There are three main variants of Arabic Language; one is Classical Arabic (CA) which was originated in the Arabian Peninsula. When literary talent and eloquence of Arabs were at their peak, Holy Qur'an was handed down to Prophet Muhammad raising an intimate relationship between Arabic language and Islam. Being complete true revelation, Holy Qur'an which contains the message of Islam is itself a miracle [1].

One of the traditions attributed to the prophet Muhammad is "the best among you is the one who learns and teaches the Qur'an". Al Norania rule (Al Qaeda Al Norania) as a systematic method developed by Sheikh Nour Muhammad Hakany to teach the right pronunciation of Arabic phonemes and syllables (speech units either separated or concatenated). It is composed of 16 lessons, each of them introduces at least one pronunciation rule. Lessons of Al Qaeda Al Norania are very suitable for children and non-native Arabic readers as they introduces the separated speech units then proceed with the composite words [2-3].

Mel-Frequency Cepstral Coefficients (MFCC) extracted from phonemes and syllables of Al Qaeda Al Norania are chosen to be the speech features to be used with Hidden Markov Model Toolbox (HTK) for the aim of Speech Verification in the learning process of Al Qaeda Al Norania.

1.1 Thesis Objective

Correct pronunciation is an essential component in learning any language. The objective of this thesis is to generate a verification model for Arabic phonemes and syllables extracted from Al Qaeda Al Norania Lessons; to detect how close the trainee's pronunciation is to the reference reader.

The Verification task is implemented through three main steps:

1. Preprocessing stage
2. Feature Extraction
3. Pattern Recognition

This study is part of an integrated set of studies on achieving proficiency in Arabic and the Holy Quran.

1.2 Thesis Organization

The thesis consists of five chapters organized as follows: