



SUBVOCAL SPEECH RECOGNITION USING ENGINEERED FEATURES AND DEEP LEARNING

By

Mohamed Said Elbially Elmahdy

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

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Title of Thesis:

Subvocal Speech Recognition Using Engineered Features and Deep Learning

Key Words:

Surface Electromyography; Deep Learning; Subvocal Speech.

Summary:

In this study we propose an end-to-end deep system for subvocal speech recognition. A single channel surface Electromyogram (sEMG) placed diagonally around the throat is used alongside a close-talk microphone for signal acquisition. The system was tested on a corpus of 20 words. The system classification was independent of the word level but smart enough to learn the mapping function from sound and sEMG sequences to letters, then extracting the most probable word from these letters. Different input signals and different depth levels were investigated using the deep learning model. The system was tested on ten healthy subjects (5 females, 5 males). The proposed system achieved a Word Error Rate (WER) of 9.44, 8.44 and 9.22 for speech, speech combined with single channel sEMG and speech with two channels of sEMG, respectively.

In order to compare the system with the results from literature, a wide range of hand crafted features were extracted and tested with Support Vector machine (SVM) and K-Nearest Neighbors. Results were comparable to those reported in literature.



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Dedication

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Table of Contents

ACKNOWLE	EDGMENTS	I
DEDICATIO	N	III
TABLE OF C	CONTENTS	V
LIST OF TAI	BLES	VIII
LIST OF FIG	SURES	IX
NOMENCLA	TURE	XI
	: INTRODUCTION	
1.1.	MOTIVATION	1
1.2.	GOAL OF THIS RESEARCH	
1.3.	STRUCTURE OF THE THESIS	2
1.4.	MAIN CONTRIBUTION OF THIS WORK	2
CHAPTER 2	: LITERATURE REVIEW	3
2.1.	SILENT SPEECH INTERFACE	3
.2.1.1	Electroencephalogram (EEG) Signal	4
2.1.2.	Surface Electromyogram (sEMG)	6
2.1.3.	Tongue based systems	
2.1.3.1.	Electromagnetic Articulograph	
2.1.3.2. 2.1.4.	Ultrasound Non Audible Murmur (NAM) microphone	
CHAPTER 3	: MEDICAL AND TECHNICAL BACKGROUND	
3.1.	MUSCLE PHYSIOLOGY AND ANATOMY	17
3.2.	SURFACE ELECTROMYOGRAPHY ACQUISITION	
3.2.1.	Equipment	
3.2.2.	Electrodes	19
3.2.2.1.	Dry and gelled electrodes	
3.2.2.2.	Electrode Properties	
3.2.2.3. 3.2.3.	Electrode PlacementsEMG signal characteristics	
3.2.3.1.	Factors affecting sEMG	
3.2.3.2.	Noise affecting sEMG	
3.2.4.	sEMG Preprocessing	23
3.2.4.1.	Filtering	
3.2.4.2.	Normalization	
3.3.	SPEECH PRODUCTION	
3.3.1.	Human Speech Organs	
3.4.	AUTOMATIC SPEECH RECOGNITION (ASR)	
3.5.	DEEP LEARNING	25

3.5.1.	Deep Neural Network	25
3.5.2.	Convolutional Neural Network	25
3.5.2.1.	Convolution Layer	26
3.5.2.2.	Filter Depth	26
3.5.2.3.	Filter Stride	
3.5.2.4.	Zero Padding	
3.5.3.	Non-Linear Activation Functions	
3.5.3.1.	Sigmoid	
3.5.3.2.	Tanh	
3.5.3.3.	Rectified Linear Unit (ReLU)	
3.5.4.	Fully Connected Layer	
3.5.5.	Recurrent Neural Network (RNN)	
3.5.6.	Long Short Term Memory Network	31
3.5.7.	Bidirectional LSTM	33
3.5.8.	Connectionist Temporal Classification Layer (CTC)	34
3.5.9.	Example For Training Deep Learning Model	34
CILA DEED 4		
	: SUBVOCAL SPEECH RECOGNITION USING ENC	
FEATURES VL	A SURFACE ELECTROMYOGRAPH	37
4.1.	Introduction	37
4.2.	MATERIALS AND METHODS	38
4.2.1.	Corpus Design	38
4.2.2.	Subjects	
4.2.3.	Signal Acquisition	
4.2.4.	Experimental Protocol and Data Labeling	
4.2.5.	Feature Extraction	
4.2.5.1.	Time Domain Features	
4.2.5.1.1.	Integrated EMG	
4.2.5.1.2.	Mean Absolute Value (MAV)	42
4.2.5.1.3.	Simple Square Integral	42
4.2.5.1.4.	EMG Variance	
4.2.5.1.5.	Root Mean Square	
4.2.5.1.6.	Waveform Length	
4.2.5.1.7. 4.2.5.1.8.	Slope Sign Changes Skewness	
4.2.5.1.6. 4.2.5.1.9.	Kurtosis	
4.2.5.1.10.		
4.2.5.2.	Frequency domain features	
4.2.5.2.1.	Zero Momentum	
4.2.5.2.2.	First, Second, and Third Momentum	45
4.2.5.2.3.	Central Frequency Variance	
4.2.5.2.4.	Mean Power	
4.2.5.2.5.	Total Power	
4.2.5.2.6.	Median Frequency	
<i>4.2.5.2.7.</i> <i>4.2.5.2.8.</i>	Mean Frequency	
4.2.5.3.	Peak frequency Mel Frequency Cepstral Coefficients	
4.2.6.	Classification Algorithms	
4.2.6.1.	Support Vector Machine (SVM)	
4.2.6.2.	K-Nearest Neighbors (KNN)	
4.3.	RESULTS	
4.3.1.	Time Domain Results	
4.3.2.	Frequency Domain Results	