

IMPROVING INTER-PERSON AMERICAN SIGN LANGUAGE
RECOGNITION ACCURACY USING DEEP LEARNING

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**IMPROVING INTER-PERSON AMERICAN SIGN LANGUAGE
RECOGNITION ACCURACY USING DEEP LEARNING**

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DEDICATION

This study is dedicated to my parents and my friends, who gave strength to me and shared their words of advice and encouragement to finish this study.

ABSTRACT

Most of the normal people don't understand sign languages performed by deaf-mute people, thus a sign language to text/voice conversion systems would greatly improve the communications between them. Hence, deep learning-based sign language system is proposed to recognize the muscle signal into a different type of American Sign Language. Deep Feed-Forward Neural Network (DFFN) and Shallow Convolutional Neural Network (SCNN) are used for this study. The proposed model evaluated with collected datasets from six subjects. A Myo Armband is used to collect the sEMG from right forearm for ten different sign language. Two experiments are conducted to evaluate the performance of both networks in intra-person and inter-person. SCNN has higher accuracy (99.7%) than DFFN (87.93%) in intra-person. However, there is no significant difference in both networks in the inter-person. Both the DFFN and SCNN show an improvement in the accuracy for inter-person by 5.82% and 5.62% respectively when more subjects are included in the training datasets. Based on the result, the inter-person accuracy can be improved by using a generalized dataset.

ABSTRAK

Kebanyakan orang biasa tidak memahami bahasa isyarat yang dilakukan oleh orang pekak-pekak, oleh itu sistem penukaran bahasa isyarat kepada tek /suara akan meningkatkan komunikasi antara mereka. Oleh itu, sistem bahasa isyarat berasaskan “deep learning” dicadangkan untuk mengiktiraf isyarat otot ke dalam pelbagai jenis Bahasa Isyarat Amerika. “Deep Feed Forward Neural Network” (DFFN) dan “Shallow Convolutinoal Neural Network” (SCNN) digunakan untuk kajian ini. Model yang dicadangkan dinilai dengan kumpulan data yang dikumpul dari enam subjek. A Myo Armband digunakan untuk mengumpul sEMG dari lengan kanan untuk sepuluh bahasa isyarat yang berbeza. Dua eksperimen dijalankan untuk menilai prestasi kedua-dua “network” dalam intra-orang dan antara orang. SCNN mempunyai ketepatan yang lebih tinggi (99.7%) daripada DFFN (87.93%) dalam intra-orang. Walau bagaimanapun, tidak terdapat perbezaan yang signifikan dalam kedua-dua rangkaian di antara orang. Kedua-dua DFFN dan SCNN menunjukkan peningkatan dalam ketepatan untuk setiap orang sebanyak 5.82% dan 5.62% apabila lebih banyak mata pelajaran dimasukkan ke dalam kumpulan latihan. Berdasarkan hasilnya, ketepatan antara orang dapat ditingkatkan dengan menggunakan dataset umum.

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LIST OF SYMBOLS AND ABBREVIATIONS

ANN	:	Artificial Neural Network
ASL	:	American Sign Language
CNN	:	Convolutional Neural Network
DFFN	:	Deep Feed Forward Network
IMU	:	Inertial Measurement Units
LDA	:	Linear Discriminant Analysis
MAV	:	Mean Absolute Value
RMS	:	Root Mean Square
SCNN	:	Shallow Convolutional Neural Network
sEMG	:	Surface Electromyography
SLR	:	Sign Language Recognition
SVMs		Support Vector Machines
WL	:	Waveform Length
WT	:	Wavelet Transform

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CHAPTER 1

INTRODUCTION

This chapter presented the general view of the project following with the background and problem statement. Objectives and scopes of the project also discussed in this chapter. All the details for each section of the project have been commented in this chapter.

1.1 Project Overview

World Health Organization (WHO) mentioned there are more than 360 million people across the world suffers from hearing impairment [1]. Furthermore, according to the World Federation of the Deaf, there are 70 million deaf people use sign language as their mother tongue. However, the lack of a common language between the deaf-mute and normal people resulting in general communication hardship [2]. Sign language is often thought of in the context of the deaf-mute community. Instead of

hearing loss, there also have several conditions where sign language is beneficial to people who aren't deaf. The reasons people use sign language other than hearing loss are autism, apraxia of speech, cerebral palsy and Down syndrome.

Since American Sign Language (ASL) is one of the most popular sign languages, so this study focused on ASL recognition. Table 1.1 shows that although many sign languages of macro-communities exert an influence on other sign languages in this way, ASL appears to be the most frequent example [3].

Table 1.1: An overview of foreign sign languages introduced to signing communities in Africa [3]

Country	Sign Language
Botswana	American SL, Danish SL, German SL
Ethiopia	Swedish SL, Finnish SL, American SL
Gambia	Dutch SL, British SL
Mali	American SL, French SL
Nigeria	American SL
Tanzania	American SL, Swedish SL, Finnish SL

The people who hard of hearing need a communication method which allows them to communicate with others to accomplish their daily tasks. Sign Language Recognition (SLR) system is a method which allows deaf-mute people to communicate with society. In this study, Sign Language Recognition system was proposed by using the surface Electromyography (sEMG). The sEMG signal acquired from the user's forearm using Myo Armband as the sensor. A sign language recognition system translates sign language performed by deaf-mute people into text and speech in real time.

Therefore, in this real-time sEMG-based ASL recognition using a deep learning neural networks project, both deep feed-forward neural network (DFFN) and shallow

convolutional neural network (CNN) technique will be explored for sEMG signal recognition with up to 10 sign languages. The method will be applied to a collected dataset to check its implementation. DFFN is implemented with Tensorflow, which is an open source library which is provided by Google to help the researchers in the machine learning projects. However, SCNN is implemented with PyTorch, which is an open source machine learning library for Python, based on the Torch that developed by Facebook's artificial-intelligence research group.

1.2 Problem Statement

There is a communication gap or ideas sharing obstacle and collaboration problem for the deaf-mute community and people who can speak and hear since not everyone learns sign language. However, the successful sEMG-based sign language recognition by computer systems would greatly improve communications between the deaf-mute and the ordinary people. There are many researchers reached a high accuracy on intra-person sign language recognition, but a great improvement on inter-person sign language recognition is required. This thesis can become one of the research resources to implement a better accuracy system for inter-person ASL recognition to enlarge the range of users.

1.3 Objectives

There are two objectives in this project listed below:

- i. To investigate Surface Electromyography (sEMG) signals recognition algorithm for ASL using deep learning.
- ii. To improve the inter-person ASL recognition accuracy using deep learning.

1.4 Scope of Project

This project is intended to implement deep learning algorithms that able to classify different ASL by using collected sEMG signals as input. Python as the main programming language in this project. Besides, the training phase is undergoing with DFFN and SCNN respectively. Tensorflow is the library for DFFN and PyTorch is the library for SCNN. The experimental paradigm is designed to record 10 classes of ASL sEMG signals over 6 able-body participants. More subjects are encouraged to add in for developing a large ASL dataset. There are also can be a large improvement to add more ASL classes. There is a limitation because of the limited budget, only one Myo Gesture Control Armband as the sensor to collect Surface Electromyography (sEMG) signals sensor so that my study focuses on the right hand. Thus, only sign language gestures with one hand can be recognized.

1.5 Project Significance

Previously, many researchers investigate the image classification method using CNN that sign language is recognized by classifying images. However, it is difficult to capture a clear picture for identifying the specific hand gesture at the crowd, there are too many affecting factors inside a picture that cause noise. To avoid affecting factor, this project is using a wearable Myo armband to collect surface electromyography (sEMG) signals from muscles and deep learning neural network to process datasets. Therefore, the significance of this project is to allow the researchers to improve the accuracy of ASL by using Myo armband and the deep learning algorithms.

Between, based on previous studies, the inter-person ASL recognition's accuracy is lower if compared to the accuracy of intra-person ASL recognition. Deep learning

is a computational model that having numerous processing layers to learn information with different features [4]. A well-defined dataset also one of the crucial factors toward the recognition's performance. Thus, this project aims to improve the performance of inter-person ASL recognition by investigating and optimizing the parameter of deep learning algorithms.

1.6 Expected Outcome

The expected outcome for this project is to investigate a deep learning algorithm to recognize ASL accurately. Datasets of sEMG signals will be trained into models using deep learning framework. Then, the system able to identify an individual's sign languages in real time when they are wearing the Myo armband. At last, the accuracy of the inter-person ASL recognition will be improved.

1.7 Thesis Outline

This thesis comprises of five chapters which Chapter 1 introduces the project. The sessions described in Chapter 1 are project overview, objectives, problem statement, scope of project, project significant as well expected outcome. Chapter 2 presents the background study about the sEMG model for ASL, the concept of deep learning neural network and related works of sEMG signals recognition. In Chapter 3, the overall flow of project methodology, which include experimental design to acquire sEMG data and the data arrangement. Chapter 4 is the discussion of the result analysis in the project. Lastly, Chapter 5 delivers the conclusion for this project. Recommendations for future works have been evaluated and commented at the end of this chapter.