Sign Language Recognition System using SEMG and Hidden Markov Model

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Abstract: - Sign language is a method of communication for the hearing-impaired. This paper proposes a recognition system which helps to translate the performed American Sign Language (ASL) gestures into texts. It is designed to capture the forearm surface electromyogram (sEMG) as the input and uses the Hidden Markov Model (HMM) as the classifier. The results are displayed on graphical user interfaces (GUIs), developed using Microsoft Visual Studio 2010. The system is reported to obtain an accuracy of approximately 94% in recognizing single characters of the ASL.

Key-Words: - Recognition system, American Sign Language, surface electromyogram, graphical user interface, hidden Markov models

1 Introduction

According to World Health Organization (WHO), there are approximately 278 million people with moderate-profound hearing impairment in 2005 [1]. However, sign language serves as the only communication mechanism for them. It is a non-verbal language which utilizes visual sign patterns such as hand gestures or any other parts of body to carry out the communication process and the literacy rate in the society is relatively low. As a result, there is a barrier in communication. Therefore, it is important to develop a sign language recognition system (SLR) to aid the interaction between the hearing-impaired and the society.

In the literature, two approaches are used to develop this system. The first method is Data Glove (DG) as demonstrated in the works of [2] and [3]. The second method is Computer Vision (CV) as described in the works of [4] and [5]. Although these procedures may provide the expected signal according to our requirements, there are still some limitations; (a) users are required to wear cumbersome sensors which greatly inconveniences their daily communication (b) accurate acquisition data may prove difficult due to expensive sensors (c) camera is sensitive to background noises such as background texture, colour and lightning condition (d) system portability is hindered. This paper proposes a system which is based on surface electromyography (sEMG) in gesture-to-text conversion in which the results are presented in Graphical User Interfaces (GUIs). Additionally, the system detects muscular activities for single letter (i.e “A”-“Z”) American Sign Language (ASL).

The direct sensing of muscular activities provides rich information on finger motions, hand shapes and wrist movements. Electromyography (EMG) has been widely used for the amputees to control prosthesis with their residual muscles [6]. The concept is reported by [7] to excel in sensing muscular activities. This paper consists of five sections. Section 1 gives the introduction, section 2 explains the surface electromyography signal and classifier recognition, section 3 describes the experiment, section 4 presents the results and section 5 concludes the paper.

2 Surface Electromyograph (sEMG) and Classifier

EMG is a technique which measures and records the electrical activities in the human skeletal muscles. It is performed using the EMG instrument to tabulate the recorded signal called an electromyogram. By analysing the detected signal; detection on medical abnormalities, activation level, recruitment order or biomechanics of human or animal movement can be known [8].

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Ref. [9] explains that sEMG is a non-invasive technique use in measuring muscle electrical activities which result from contraction and relaxation exercises. It is commonly used as an indicator for biofeedback, relaxation and muscle re-education. Firstly, the sEMG signals generated by the skeletal muscles are captured by the electrodes. The analogues signals are then converted to a digital signal by the encoder and be sent to the computer for further processing. The amplitude of the EMG signal is random in nature and can be represented by a Gaussian distribution function. Its peak to peak voltage ranges from 0 to 10mV or equivalent to approximately 1.5mV in rms value. The usable energy is limited to frequency below 500Hz [10]. The gathered EMG signals from the electrodes could be either positive or negative since they comprise action potentials occurring in the underlying muscles of the electrode [11].

In the works of [12] and [13], a group of muscles are represented for single character sign language. In this paper, five locations on the forearm have been found to resemble closely to the finger activities (see Fig. 1). Muscles are generally divided into two groups; superficial muscle and deep muscle. Some muscles like the *Pronator quadrates* are not directly responsible for the finger movement but are involved in the wrist movements when performing the “J” and “Z” letter. The use of different inputs can eliminate noise, amplify the signals and enhance the result.

There are two types of learning processes for classifier:

1. Supervised pattern recognition: This is used when the example patterns are known to its classes. The categorized patterns are used to train the system and the feedback allows the system to improve itself iteratively.
2. Unsupervised pattern recognition: this is used when the example patterns are not known to its classes. The system has to define the classification procedure and classes. This kind of pattern recognition is usually more difficult. However, there are some useful algorithms that have been developed to aid in the process.

There are some classification methods which are commonly used in pattern recognition system which involve the SLR. They are Support Vector Machine (SVM)[14], Artificial Neural Network (ANN) [11, 15, 16] and Hidden Markov Model (HMM). The HMM is a well-known classifier due to the robustness in the domain of signal processing.

3 Experiment

The system comprises of four steps: data capturing, data processing, system training, and system verification. This system consists of two main components: hardware (required for data capturing) and software (from data processing to recognition). The overall system is illustrated in Fig. 2.

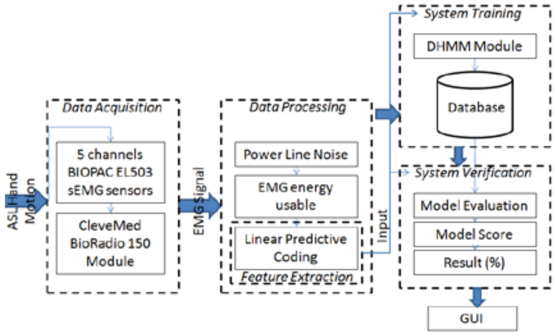

Fig. 1 The Sign Language Recognition System Architecture

3.1 Data Capturing

The dataset used in this paper are collected from the Centre Biomedical Engineering (CBE) room with the average temperature between 21 to 23 °C. The instrument is placed far from all radio frequency (RF) emitting devices. The subject (a normal right-handed, 23 years old man with no medical history) is seated comfortably on a chair and the shoulder has to be parallel to the table line with his right hand placed on the table. Prior to the data acquisition, the required list of ASL is shown and demonstrated to the subject.

ASL is grouped into three categories, (a) all

Fig. 2 Electrode position to record sEMG data

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characters (i.e “A” to “Z”) (b) distinct sign letters: B, G, J, K, M, R, X and Z and (c) similar sign letters: A, C, E, M, N, O, S, and T [17]. The gestures in the three categories are then performed and captured using the sEMG sensors (Biopac EL503) and CleveMed BioRadio 150 module with 960Hz sampling rate. Each gesture is recorded for 2 seconds and the subject has to resume to the initial posture before the next capturing.

3.2 Data Processing

In this stage, the 50Hz power line noise is removed and the EMG usable energy range between 50 to 150Hz was filtered out. Feature extraction (Linear Predictive Coding, LPC) is performed by extracting some important features that represent the signals.

3.3 System Training

The database is based on supervised pattern recognition process using half of the sample data. According to the discrete Hidden Markov Model (DHMM), samples of the same attributes are classified within the same class. The DHMM are produced as a result of training the data inputs using Vector Quantization (VQ) and managed to produce 128 classes. The training in this stage is performed using Training Tools Software developed by CBE-UTM research group [3].

3.4 System Verification

The system is tested using ten additional samples as the inputs for further verification. A GUI (see Fig. 3) is developed to display the recognition result. It is used to observe the analysis of the system performance and recording down the accuracy of the recognition for each sign. The performance of the system is tabulated in Table 1.

4 Result and Discussion

Table 1 describes the results obtained from the system and records an overall recognition accuracy of approximately 94%. This confirms that sEMG can be used as an alternative solution in implementing more robust sign language recognition system compared to DG and CV method.

Table 1 The result of accuracy ASL

ASL Sign	Recognized Wrongly As	Accuracy (%)
B		100
G	Z	90
J		100
K		100
M		100
R	J	80
X	M, G	80
Z		100
Overall		93.75

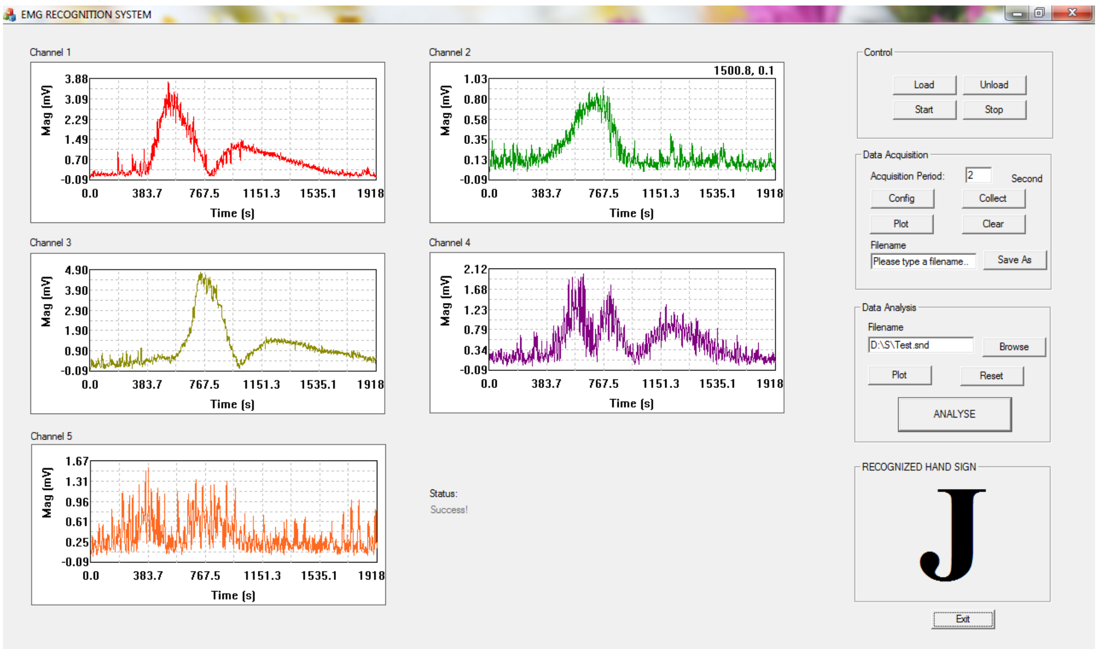

Fig. 3 GUI interface to interact with the CleveMed BioRadio 5 channels, display the data of each channels, and recognized signal

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5 Conclusion

The implemented system which applies sEMG and utilizes HMM model as classifier is reported to perform well in recognizing single character ASL. Additionally, the results are well presented through the usage of GUIs. For future works, more sEMG systems for sign language recognition can be studied and developed in order to reduce the communication barrier.

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