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Hand Gesture Recognition for Post-stroke Rehabilitation Using Leap Motion

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Abstract

In order to enhance and/or improve recovery after stroke, rehabilitation needs to start early and be monitored by continuous and recurrent long-term interventions in the clinic and home setting. The elderly is a high risk stroke group with advancing age, resulting in increasing demand of strengthened resource of hospitals and physiotherapist. The residential rehabilitation for stroke patients would effectively relieve shortages of medical resources. However, the residential rehabilitation for stroke patients faces with the lack of professional guidance, and physiotherapist cannot monitor the rehabilitation progress of stroke patients. These problems may lead to additional harm or deteriorate rehabilitation progress. In order to solve this problem, we develop a hand gesture recognition algorithm devoted to monitor the seven gestures for residential rehabilitation of the post-stroke patients. The gestures were performed by seventeen healthy young subjects. The results were assessed by k-fold cross validation method. The results show that the proposed hand gesture recognition algorithm using multi-class SVM and k-NN classifier achieve accuracy of 97.29% and 97.71%, respectively.

Key words: stroke rehabilitation, gesture recognition, machine learning, leap motion

Introduction

According to the World Health Organization (WHO), stroke is the second leading cause of death in the world. About 56.4 million deaths worldwide in 2015, 11% of them were due to stroke and accounting for 6.24 million deaths [1]. Stroke is also a leading cause of long-term disability. Up to approximately 85% of stroke survivors, resulting in limitation in upper limb function [2]. Rehabilitation is the essential strategy for upper limb function recovery.

Evaluations of post-stroke rehabilitation include questionnaires, self-report and assessment tools such as Fugl-Meyer Assessment (FMA), Motor Assessment Scale (MAS) and Brunnstrom Recovery Scale. Most of the treatment protocols are labor intensive and require 1-to-1 manual interaction with therapists for each treatment. As a result, stroke patients need to spend lots of round-trip time between home and hospital. Although traditional assessment methods have been proposed and evaluation results are accepted widely, they still exist some problems such as subjective assessment, shortages of human resource and time consuming.

In order to solve these problems, many researches attempt to record the process of rehabilitation using somatosensory devices (e.g. Wii, Kinect) [3, 4], and send the information to the hospital by internet. Clinical professional physiotherapist can then monitor the process of rehabilitation to guide and/or adjust the steps of rehabilitation in time. Recently, Maryam et al. [5] have tracked the hand posture using the Leap Motion controller for stroke patients with hand weakness. The results showed a significant correlation between standard clinical outcome measures and scores generated from the Fruit Ninja game. Another research of motor rehabilitation system is VirtualRehab [6] which contains many therapeutic game using Kinect and Leap motion for stroke patients. VirtualRehab involved exercises such as intensive flexion and extension movement of fingers and the wrist based on clinical demands. The study showed it feasibility of free-hand interaction technologies that can be applied to residential rehabilitation of stroke patients due to remarkable hand gesture recognition. However, the residential rehabilitation for stroke patients faces with the lack of professional guidance, and physiotherapist cannot monitor the rehabilitation progress of treatment. These problems may lead to additional harm or deteriorate rehabilitation progress.

In this work, we develop a hand gesture recognition algorithm devoted to monitor the seven gestures for residential rehabilitation of the post-stroke patients. The seven gestures include extension-flexion, close and spread fingers, fingertip tap, radial-ulnar deviation, fingertip touch, palm rotation and finger mass extension-flexion. The seven gestures are shown in Fig. 1. Each gesture is a simple and, more importantly, patient-directed treatment that may improve hand functions [6]. The gestures were performed by seventeen healthy young subjects (15 males and 2 females, 23-27 years old). The results were assessed by k-fold cross validation method. The results show that the proposed hand gesture recognition algorithm using multi-class support vector machine (SVM) and k nearest neighbor (k-NN) classifier achieve accuracy of 97.29% and 97.71%, respectively.

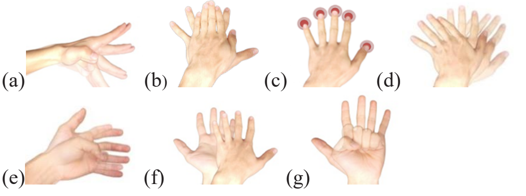

Fig. 1 The seven different gestures. (a) extension-flexion of wrist (b) close and spread fingers (c) fingertip tap (d) radial-ulnar deviation (e) fingertip touch (f) palm rotation (g) finger mass extension-flexion.

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Materials and methods

A. Hand gesture recognition algorithm

The functional diagram of the proposed hand gesture recognition algorithm is shown in Fig. 2. There are two phases in this algorithm; one is the training phase, the other is testing phase. There are two main stages including feature extraction and gesture model training in training phase.

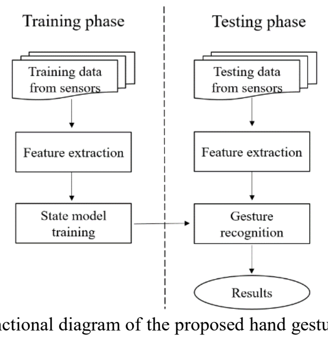

Fig. 2 The functional diagram of the proposed hand gesture recognition algorithm.

Firstly, a leap motion controller is utilized to record the motions of hand gesture with 60 Hz sampling rate. In this study, we mainly focus on the following data: Positions of the fingertips F_i, i = 1, …, 5. Vectors F_i containing the 3D positions of each detected fingertips. Wrist center C that represent the 3D location roughly corresponding to the center of the wrist region in the 3D space. In order to avoid missing motions of hand gesture and in accordance to experimental settings, the participants are asked to put hands 20cm above the leap motion controller. The Leap Motion Controller is a device for hand gesture controlled user interfaces with declared sub-millimeter accuracy [7].

The device consists of two stereo cameras and three infrared LEDs. These tracks infrared light with a wavelength of 850 nanometers, which is outside the visible light spectrum. The x-axis and z-axis lie in the horizontal plane, and the x-axis runs parallel to the long edge of the device. The coordinate of leap motion is shown in Fig. 3.

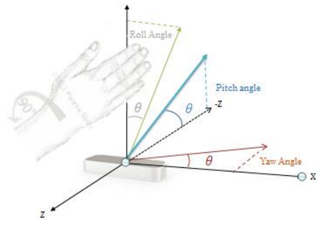

Fig. 3 Cartesian coordinate system of leap motion

In feature extraction, 17 features are extracted including Euclidean distances between the fingertips, pitch angle of palm, yaw angle of palm, roll angle of palm, and angles between fingers. There are ten features including the Euclidean distances between thumb-index, thumb-middle, thumb-ring, thumb-pinky, index-middle, index-ring, index-pinky, middle-ring, middle-pinky, ring-pinky fingertips. Distance is defined as:

$$D_{Ti} = \| F_1 - F_i \|, \text{ where i = 2, …, 5} \quad (1)$$

$$D_{Ii} = \| F_2 - F_i \|, \text{ where i = 3, 4 and 5} \quad (2)$$

$$D_{Mi} = \| F_3 - F_i \|, \text{ where i = 4 and 5} \quad (3)$$

$$D_{Ri} = \| F_4 - F_i \|, \text{ where i= 5} \quad (4)$$

Where D_{Ti} are Euclidean distances between thumb-index, thumb-middle, thumb-ring, thumb-pinky. D_{Ii} are Euclidean distances between index-middle, index-ring, index-pinky. D_{Mi} are Euclidean distances between middle-ring, middle-pinky. D_{Ri} is Euclidean distance between ring-pinky fingertips.

In the pitch, yaw and roll angle of palm, the Cartesian coordinate system is shown in Fig. 3. Pitch is the angle between the negative z-axis and the projection of the vector onto the y-z plane. In the other words, pitch represents rotation around the x-axis. Pitch angle variation is between π/2 radians and – π/2 radians when extension-flexion gesture was performed. Yaw is the angle between the negative z-axis and the projection of the vector onto the x-z plane. In the other words, yaw represents rotation around the y-axis. Yaw angle variation is between π/2 radians and –π/2 radians when radial-ulnar deviation gesture was performed. Roll is the angle between the y-axis and the projection of the vector onto the x-y plane. In the other words, roll represents rotation around the z-axis. Roll angle variation is between π/2 radians and – π/2 radians when palm rotation deviation gesture was performed.

The A_i is the angle between fingers using the dot product equation. The angles between fingers are defined as:

$$A_i = \angle(F_{i+1} - C, F_i - C), \text{ where i = 1, …, 4} \quad (5)$$

In gestures model training, training a gesture model classifies the gestures using multi-class support vector machine (SVM) approach with linear kernel function and k-nearest neighbors (k-NN) approach. In gesture recognition, the trained gesture model classifies the testing data into a proper gesture.

B. Support Vector Machine

Support vector machine (SVM) is one of the classic mathematical methods and is widely used to analyze data and recognize patterns, which generally used for classification and regression analysis. The goal of SVM is to train a model that can predict the target value of data instances in the test set that are given the attributes only. In this paper, SVM is utilized to achieve multi-classification among the 7 gestures, that strives to find a separating hyperplane with the maximal margin in this high dimensional space. The linear kernel function and one-versus-one technique is adopted in this study.

C. K-Nearest Neighbors

K-nearest neighbor classifier is a machine learning technique that classifies testing data based on closest training data in the feature space. Class judgment is produced from majority voting of k nearest neighbors. The number of k is a positive integer and no standard answer, that is an issue of trade-off between sensitivity and robustness. Larger number of k decreases the sensitivity by increasing bias or noise data, whereas smaller number of k causes unstable results by increasing variance. Therefore, the number of k depends on the local dataset. The main drawback of k-NN is the complexity in searching the nearest neighbors for each testing data.

Results and conclusions

Seven kinds of rehabilitation gestures are arranged in the experiments to verify the machine learning hand gesture recognition algorithm. The gestures were performed by seventeen healthy young subjects (15 males and 2 females, 23-27 years old). The results of evaluation were obtained by k-fold cross validation method. In order to make sure that each hand gesture was used to select features and train the classification model, we chose k = 8 for k-fold cross validation method, and each subsample had at least one sample of seven kinds of hand gesture. The k-fold cross-validation method randomly partitions the collected data into k portions and utilizes k – 1 portions as training data and one portion as testing data, then repeating it k times to evaluate the results.

The total number of hand gestures are 584. Table I shows the confusion matrix of the SVM approach for each hand gesture. The total number of each hand gesture, including extension-flexion, close and spread fingers, fingertip tap, radial-ulnar deviation, fingertip touch, palm rotation, finger mass extension-flexion was 81, 82, 85, 85, 85, 85, 81, respectively. The results of accuracy with SVM and k-NN approach are shown in Table II. Accuracy is the proportion of the truth test outcome in the total results. The average accuracy of SVM and k-NN approaches are 97.29 and 97.71%, respectively.

TABLE I
THE CONFUSION MATRIX OF THE MACHINE LEARNING–BASED ALGORITHM FOR EACH HAND GESTURE.

Predicted		Hand Gesture (Ground Truth)						
		(a)	(b)	(c)	(d)	(e)	(f)	(g)
(a)	Extension-Flexion	79		3				
(b)	Close and Spread fingers	1	81		1		2	
(c)	Fingertip tap		1	82	1	5		
(d)	Radial-Ulnar deviation	1			83			
(e)	Fingertip touch					80		
(f)	Palm rotation						83	
(g)	Finger mass extension-flexion							81
	Sensitivity (%)	96	99	96	98	94	98	100

TABLE II
THE OVERALL PERFORMANCE OF THE EIGHT-FOLD CROSS-VALIDATION FOR THE MACHINE LEARNING-BASED HAND GESTURE REGONITION ALGORITHM.

Gesture	Algorithm	
	SVM	k-NN
Extension-Flexion	96%	93%
Close and Spread fingers	99%	99%
Fingertip tap	96%	98%
Radial-Ulnar deviation	98%	98%
Fingertip touch	94%	98%
Palm rotation	98%	98%
Finger mass extension-flexion	100%	100%
Average Accuracy	97.29%	97.71%

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