Data Glove System Embedded With Inertial Measurement Units for Hand Function Evaluation in Stroke Patients

Bor-Shing Lin, *Member, IEEE*, Pei-Chi Hsiao, Shu-Yu Yang, Che-Shih Su, and I-Jung Lee

***Abstract*— This paper proposes a data glove system integrated with six-axis inertial measurement unit sensors for evaluating the hand function of patients who have suffered a stroke. The modular design of this data glove facilitates its use for stroke patients. The proposed system can use the hand's accelerations, angular velocities, and joint angles as calculated by a quaternion algorithm, to help physicians gain new insights into rehabilitation treatments. A clinical experiment was performed on 15 healthy subjects and 15 stroke patients whose Brunnstrom stages (BSs) ranged from 4 to 6. In this experiment, the participants were subjected to a grip task, thumb task, and card turning task to produce raw data and three features, namely, the average rotation speed, variation of movement completion time, and quality of movement; these features were extracted from the recorded data to form 2-D and 3-D scatter plots. These scatter plots can provide reference information and guidance to physicians who must determine the BSs of stroke patients. The proposed system demonstrated a hit rate of 70.22% on average. Therefore, this system can effectively reduce physicians' load and provide them with detailed information about hand function to help them adjust rehabilitation strategies for stroke patients.**

***Index Terms*— Action monitoring, data glove, inertial sensor, hand function evaluation system, stroke.**

I. Introduction

THE problem of how to increase the effectiveness of rehabilitation and reduce the recovery time for stroke patients is faced by all hospitals worldwide. Physicians must adjust each stroke patient's therapy to reflect the patient's degree of progress in recovering hand function. Therefore, evaluating stroke patients' hand function is an essential part of rehabilitation therapy. In the past, therapists could only determine the condition of a patient if the patient has been subjected to traditional assessment tests such as the Fugl-Meyer assessment (FMA) [1], action research arm test (ARAT) [2], or Jebsen-Taylor hand function test (JTT) [3]. Determining detailed information such as acceleration, angular velocity, smoothness, and stability of a patient's hand function is difficult for therapists. Moreover, therapists face difficulties in measuring a patient's progress in recovering hand function, as well as in assessing the quality of a patient's hand movement during the rehabilitation process.

Hand function evaluation systems have been gradually adopted in the medical profession for assessing stroke patients. Such evaluation systems monitor how the situation of patients' hands changes with rehabilitation processes. In 2010, Allin *et al.* [4] proposed a system that uses a camera to track the upper limbs of stroke patients during rehabilitation actions and to evaluate the features of each patient's rehabilitation actions through image processing and analysis. Although the assessment method in this system is convenient, the factors of occlusion and lighting effects tend to reduce the system's performance and often result in the misjudgment of a patient's condition.

With technological advancement, numerous studies have reported the application of data gloves for evaluating hand function; such data gloves may include mechanical units, resistance sensing units, fiber sensing units, or inertial sensing units. Mechanical data gloves have been used to evaluate hand function for a long time. In 2009, Blake and Gurocak [5] developed a haptic glove that involved the first use of MR brakes. In 2011, Ito *et al.* [6] reported a design of fine-motion assistance equipment for hand rehabilitation, which can assist motions such as bilateral flexion, extension, abduction, individual finger adduction, and opposing motion of the thumb. Although these types of gloves can provide accurate measurement and assistance, they are bulky, expensive, heavy, and often inconvenient for patients. To reduce the weight and cost of evaluation devices, data gloves have been developed using lightweight materials such as optical fibers or resistance sensors. In 2011, da Silva *et al.* [7] used optical fiber Bragg grating sensors to develop a wearable sensing glove. The optical fiber design resolves the problems inherent in mechanical architectures; nevertheless, the optical fiber sensors are expensive and imprecise. In 2016, Yu *et al.* [8] used a glove

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with flex sensors as a part of an evaluation system. In this system, each resistance value represents the degrees of finger flexion; therefore, the resistance values can be used to measure finger flexion. These types of gloves are thin and lightweight, but they could be uncomfortable to wear and easily result in inaccurate assessments because they involve an inflexible resistance and can only measure the flexion and extension of the fingers.

Although previous sensors are cumbersome, advances in semiconductor technology have engendered miniaturized sensors. Some studies have applied inertial measurement units (IMUs) to measure hand motion. For example, in 2014, Kortier *et al.* [9] proposed an IMU-based glove system that entails using the data from accelerometers, gyroscopes, and magnetometers to measure hand kinematics. They also mentioned the possibilities and challenges to be faced in executing kinematics analyses using inertial sensing technology.

Most recent monitoring systems involve using data gloves to measure the hand motion of recovering stroke patients, but few of such systems entail using data gloves to evaluate hand function. In 2008, Alamri *et al.* [10] proposed a virtual-reality-based rehabilitation assessment system. They combined the CyberGrasp system and virtual reality to develop a series of rehabilitation games; the sensitivity and stability of a patient's hand function were evaluated from the scores, trajectories, and completion times in the rehabilitation games. However, this rehabilitation assessment system requires each patient to perform subtle movements with bulky and inconvenient equipment, which limits the locations in which the system can be deployed. In 2012, Oess *et al.* [11] used a data glove composed of bending sensors to monitor the changes in finger joint angles in a patient who performed repetitive tasks; they utilized the changes in angles derived in the repetitive tasks to derive an intraclass correlation coefficient (ICC). The ICC can be used to evaluate the similarity of each movement to another movement and to evaluate patients' hand function.

To avoid the disadvantages of previous studies, the current study proposes a data glove system embedded with six-axis IMUs for hand function evaluation. The proposed system can not only overcome the drawbacks of previous data glove systems, but also record the details of finger motions, such as acceleration, angular velocity, and range of motion (ROM); three other features can be extrapolated: the average rotation speed (ARS), variation of movement completion time (VMCT), and quality of movement (QM). These features can be used to not only determine the Brunnstrom stage (BS) of stroke patients, but also judge whether a patient's hand function has improved. A two-dimensional (2D) or three-dimensional (3D) scatter plot comprising information regarding the ARS, VMCT, and QM can also inform physicians about various aspects of the patient's hand function, such as sensitivity and stability. Therefore, the proposed data glove system provides therapists with an effective user-friendly recording and evaluation tool. Finally, therapists can use this system to analyze the recovery status of a patient's hand function; such an analysis can provide information for the selection of appropriate rehabilitation tools.

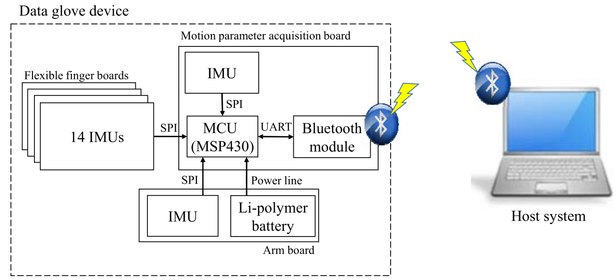

Fig. 1. System architecture.

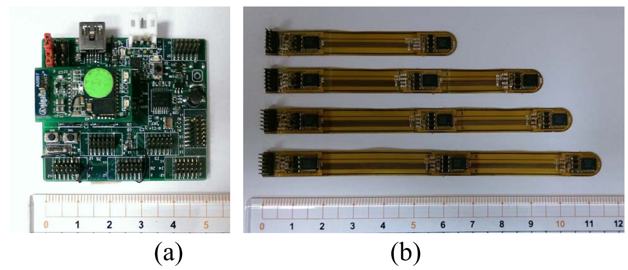

Fig. 2. Photograph of (a) MPAB, and (b) FFB.

II. Methods

A. Hardware Architecture

The proposed data glove was constructed and tested as a medical hand function evaluation system. The data glove is intended to be convenient for patients who wear it, in addition to being informative for physicians who use it to monitor the parameters of patients' hand movements, such as acceleration, angular velocity, and finger ROM. These motion parameters are useful for evaluating the quality of patients' hand movements. The proposed system consists of a motion parameter acquisition board (MPAB), flexible finger board (FFB), arm board, and host system, and Fig. 1 presents its architecture.

The MPAB, measuring 42 mm $\times$ 50 mm $\times$ 8 mm, collects inertial data from the three-axis accelerometers and three-axis gyroscopes of 16 IMU (LSM330DLC, STMicroelectronics, Geneva, Switzerland) sensors. The MPAB includes a microcontroller unit (MCU), transmission switch circuit, power management circuit, Bluetooth 2.1+EDR module (Ct-BT02, Connectec Electronics, Taiwan), and Li-polymer battery. The MCU (MSP430, Texas Instruments Inc., TI, United States) collects data from the IMU sensors through a serial peripheral interface and then transmits the encapsulated data to the host system through Bluetooth. The transmission rate of the Bluetooth module is 115200 bps. A commercial 1000-mAh Li-polymer battery provides power for at least 5 h. Fig. 2(a) depicts a photograph of the MPAB.

The FFB has 2 or 3 IMU sensors on each finger; flexible copper clads (FCCs) connect the IMU sensors to form a finger FCC strip. Four FFB components with different lengths are available. This design effectively minimizes the volume of the data glove, in addition to minimizing the load on the wearer's fingers. Fig. 2(b) depicts a photograph of the four FFB components. The arm board, which calculates the angle of the wrist joint, consists of one IMU sensor and one battery;

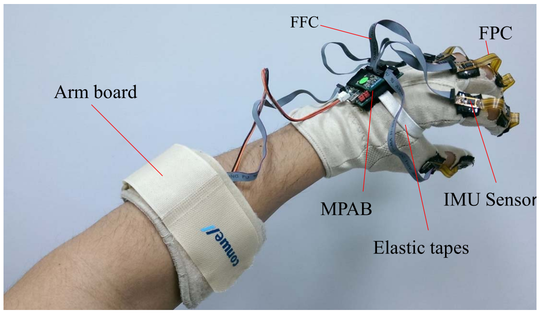

Fig. 3. Photograph of the entire assembled data glove.

it is worn on the forearm to reduce the load on the hand. The host system runs a self-developed Windows program that records the data from the data glove, calculates the finger ROM values, and helps therapists evaluate hand function in stroke patients.

B. Mechanical Design of the Data Glove

In the past, data gloves were designed in only one fixed size; nevertheless, such "one-size-fits-all" designs are not suitable for stroke patients whose hands do not match the designers' expectations. By contrast, our data glove was designed as a modular kit that can be assembled to fit hands of almost any size. One critical problem is how to place the IMU sensors at the correct positions on each finger without compromising the convenience of the device for patients and therapists.

For the experiments of the present study, transparent soft plastic strips were sewn onto an elastic fabric; the IMU sensors were attached to the transparent soft plastic by using strong double-sided tape (Polar Bear SR-6600 Double-Sided Tape, New Taipei City, Taiwan); elastic tape was sewn between the two edges of the elastic fabric to form a circular ring. Fig. 3 presents a photograph of the entire assembled data glove.

Previously developed data gloves have several problems: Some of such gloves are difficult to clean, some restrict patient hand mobility, and some are excessively inconvenient. Our proposed modular design ameliorates these problems. Because the sensors are only attached to the glove by elastic tape, each finger FPC can be conveniently replaced if any IMU sensor or other element is damaged.

C. Software Design

The operating system of the device is Windows 7. The data-glove-based hand function evaluation software system comprises two major parts, namely an angle calculation program and an evaluation program.

The angle calculation program calculates the ROMs of a patient's fingers. The program was developed in Microsoft C#. It first calibrates the acceleration and angular velocity data received from the sensors and then uses an algorithm to calculate the finger ROMs. The evaluation program analyzes the motion parameters from recorded data in order to calculate hand mobility, hand motion stability, and other aspects of hand function. The program was developed in Matlab (Matlab, MathWorks Inc., MA, United States) and can visualize the analysis results as scatter plots in a 2D or 3D feature space. All raw data, motion features, and scatter plots can be stored in hospital databases to support medical diagnoses and to help therapists in selecting suitable rehabilitation exercises during rehabilitation treatment.

D. Finger ROM Estimation Algorithm

The current study referred to numerous previous studies associated with algorithms dealing with trigonometric functions and with quaternion algorithms that can be used to derive the finger ROM between two IMU sensors by calculating the Euler angles of each sensor. Accordingly, the proposed data glove system includes two main parts: a quaternion algorithm and a finger ROM algorithm.

The quaternion $Q = (q_0, q_1, q_2, q_3)$ can be regarded as a combination of a scalar component q_0 and a vector component $q = (q_1, q_2, q_3)^{\mathrm{T}}$. This study adopted the efficient and stable quaternion algorithm proposed by Madgwick *et al.* [12]; this algorithm applies Mahony's complementary filter to correct the accelerometer and gyroscope readings and thus obtain the value of quaternion Q.

A triaxis gyroscope is first used to measure the angular rates of all axes of the sensor frame, which are termed g_x, g_y, and g_z. The parameters are arranged within vector ${}^{S}\omega$, as defined in (1). The quaternion derivative describing the rate of change associated with the earth frame relative to the sensor frame ${}^{S}_{E}\dot{q}$ can be calculated using (2). The $\times$ operation denotes a quaternion and the $\widehat{}$ accent denotes a normalized vector of unit length.

$$ {}^{S}\omega = (0, g_x, g_y, g_z) \tag{1} $$

$$ {}^{S}_{E}\dot{q} = \frac{1}{2}{}^{S}_{E}\widehat{q} \times {}^{S}\omega \tag{2} $$

The orientation of the earth frame relative to the sensor frame at time t, ${}^{S}_{E}q_{\omega,t}$, can be computed by numerically integrating the quaternion derivative ${}^{S}_{E}\dot{q}_{\omega,t}$ using (3) and (4), provided that the initial conditions are known.

$$ {}^{S}_{E}\dot{q}_{\omega,t} = \frac{1}{2}{}^{S}_{E}\widehat{q}_{t-1} \times {}^{S}\omega_t \tag{3} $$

$$ {}^{S}_{E}q_{\omega,t} = {}^{S}_{E}\widehat{q}_{t-1} + {}^{S}_{E}\dot{q}_{\omega,t} \cdot \Delta t \tag{4} $$

${}^{S}\omega_t$ is the angular rate measured at time t, Δt is the sampling period, and ${}^{S}_{E}\widehat{q}_{t-1}$ is the previously estimated orientation. The subscript ω indicates that the quaternion is calculated from angular rates.

Regarding the finger ROM algorithm, the calculation of 14 finger ROMs and 1 wrist ROM relies on two IMU sensors on either side of the interphalangeal joint. The conversion between quaternion and Euler angles is used to compute the pitch, roll, and yaw of the Euler angles from the quaternion of the sensor frame, as presented in (5)–(7).

$$ Pitch = \tan2^{-1}\left(\frac{2\,(q_0q_2 - q_1q_3)}{1 - 2q_2^2 - 2q_1^2}\right) \tag{5} $$

$$ Roll = \sin^{-1} 2\,(q_2q_3 + q_0q_1) \tag{6} $$

$$ Yaw = \tan2^{-1}\left(\frac{2\,(q_1q_2 - q_0q_3)}{2q_0^2 + 2q_1^2 - 1}\right) \tag{7} $$

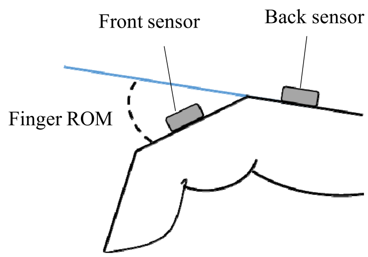

Fig. 4. Calculation of finger ROM.

TABLE I
PARTICIPANTS' CHARACTERISTICS

	Healthy subjects (HS1~HS15)	Stroke patients (SP1~SP15)
Age	62.6 ± 12.6	59.3 ± 16.3
Gender	Male × 5 Female × 10	Male × 9 Female × 6

The IMU sensor measuring the proximity to the fingertip is the front sensor, and the IMU sensor measuring the proximity to the metacarpophalangeal joint is the back sensor. The pitch angles of the front and back sensors can be used to calculate the finger ROM, as shown in Fig. 4.

III. Clinical Experiment

A. Participants' Characteristics

This study conducted a clinical experiment involving 15 healthy elderly subjects (denoted as HS) and 15 stroke patients (denoted as SP) to examine the effectiveness of the proposed system. The age of the subjects was distributed from 43 to 73, and the age difference between the healthy and stroke groups was nonsignificant ($p = 0.3648$). TABLE I presents the subjects' characteristics.

Therapists can grade stroke patients according to their BSs, based on the recovery of six features after stroke [13]. Each BS is described in TABLE II. Accordingly, for the participants in TABLE I, SP1 could be classified as being in BS6, SP2–SP11 as being in BS5, and SP12–SP15 as being in BS4. Because stroke patients classified in BS6 have almost the same level of hand function as that of healthy people, most of such patients had already been discharged from their various hospitals during the execution of the clinical experiment. Relatively few stroke patients were classified as being in BS6. Therefore, only one stroke patient classified as being in BS6 was available to join the experiment and was added to the HS group in the analysis. All experiments were approved by the Institutional Review Board (IRB No.10102-019) of Chi Mei Hospital.

B. Experimental Tasks

In the clinical experiment, all participants performed three tasks: a grip task (GT), thumb task (TT), and card-turning task (CTT). Various clinical assessments were conducted, including the JTT and a grip–release test.

The GT is a repeatable extension/flexion motion task [14], which could also be applied as a grip–release task, using the

TABLE II
BS DESCRIPTION [13]

Stage	Description
1	Immediately following a stroke there is a period of flaccidity whereby no movement of the limbs on the affected side occurs.
2	Recovery begins with developing spasticity, increased reflexes and synergic movement patterns termed obligatory synergies.
3	Spasticity becomes more pronounced and obligatory synergies become strong.
4	Spasticity and the influence of synergy begins to decline and the patient is able to move with less restrictions.
5	Spasticity continues to decline, and there is a greater ability for the patient to move freely from the synergy pattern.
6	Spasticity is no longer apparent, allowing near-normal to normal movement and coordination.

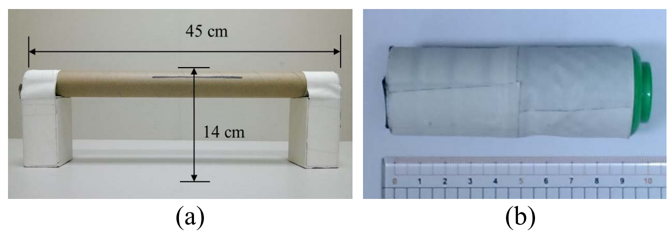

Fig. 5. (a) GT apparatus, and (b) TT apparatus.

device shown in Fig. 5(a). In the GT, the subject was reminded by a ringing sound every 4 s. A completed motion was defined to include both a grip action and a release action. This task was repeated 10 times over a period of approximately 2 min.

The TT involved subject gripping a cylinder and then clicking a push-button on the cylinder using his or her thumb. Fig. 5(b) illustrates the apparatus used in the TT. In this task, the subject was also reminded by a ringing sound every 4 s. A completed motion was defined to include both a press action and a release action. When the subject moved his or her thumb up and down on the push-button, the fingers were taken to the limit of their stretching ability. This task was repeated 10 times over a period of approximately 2 min.

The CTT involved the subject turning a card (3 in × 5 in) 20 times. During the experiment, the subject must be careful of two actions. The first action involved straightening all of the fingers except the thumb and placing the card on the table, and the second action involved turning the card by flexing the finger while placing (not throwing) the card on the table. The aim of the CTT was to compare the hand flexion of the healthy subjects with that of the stroke patients. This task was repeated 20 times over a period of approximately 1.5 min.

These simple tasks can be understood by stroke patients with weak cognitive abilities. Furthermore, various aspects of the data obtained from these tasks can be used in the evaluation of stroke patients' hand function.

C. Feature Extraction

In this study, the parameters of repetitive movements involved in a variety of tasks, including acceleration, angular

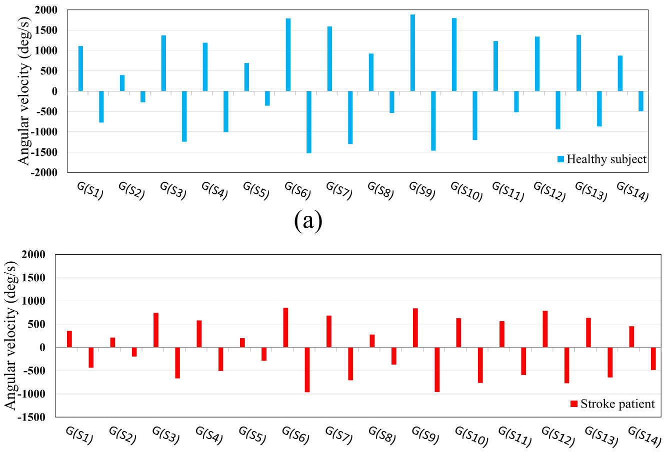

Fig. 6. (a) Average angular velocities as demonstrated by a healthy subject, and (b) average angular velocities as demonstrated by a stroke subject.

velocity, and finger ROM, were analyzed. Matlab was used to extract and calculate the features, three of which are outlined as follows:

The ARS (measured in degree per second) is a feature of hand mobility, and in this study, it was derived according to the changes in the angular velocity along the y-axis of a subject's hand during the GT and TT.

The grip movement involves finger flexion and extension. If the finger flexes, the angular velocity is positive, but if the finger extends, the angular velocity is negative. The range of angular velocity in one grip movement can be derived as the set of differences between the maximum angular velocity and the minimum velocity in all IMU sensors. The ARS value can be derived as the average difference in angular velocity for 14 IMU sensors in the GT and TT, as presented in (8).

$$ARS = \frac{1}{14}\sum_{i=1}^{14} \frac{\max\left[G\left(S_i\right)\right] - \min\left[G\left(S_i\right)\right]}{2} \tag{8}$$

where S_i represents the position of the IMU sensor, with five fingers having 14 sensors; $G\left(S_i\right)$ represents the average angular velocity of the ith sensor derived after 10 actions; $\max[G(Si)]$ represents the maximum average angular velocity of a sensor in the S_i position; and $\min[G(Si)]$ represents the minimum average angular velocity (a negative value) of a sensor in the S_i position, when the fingers are stretched to the greatest possible extent. Therefore, the ARS values associated with the GT and TT provide quantitative indications of mobility. As shown in Fig. 6, in this study, the average difference in the angular velocity of a healthy subject was higher than that of a stroke patient; thus, the ARS of a healthy subject was higher than that of a stroke patient.

The VMCT is a characteristic of hand stability that reflects the time required to complete the turning of each card; in this study, it was based on statistical variations observed when a subject took the CTT. Fig. 7 illustrates the distribution of completion times associated with each movement, as performed by the healthy subjects and stroke patients. Because the movements of the healthy subjects were stable, the changes in completion time and variance were both small.

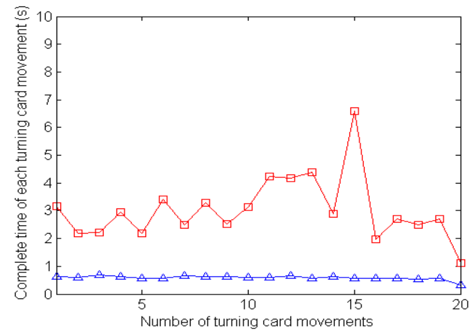

Fig. 7. Distribution of completion times for a healthy subject and a stroke patient.

By contrast, because the stroke patients performed the CTT at different speeds, the execution times of each patient's actions and the average time of 20 actions showed large differences. Therefore, the variance was higher and reflected the instability of hand function.

In the past, the families of stroke patients and the patients themselves had no clear idea of hand stability. The VMCT is a quantitative indication of stability that can represent the degree of stability for each subject. The variance value associated with the completion of CTT over 20 trials provides a quantitative indication of stability.

The QM indicates the smoothness in hand movement. In the present study, the QM was extracted by observing changes in the finger ROM of the proximal interphalangeal (PIP) joint in the CTT. Because previously developed data glove systems do not evaluate the quality of patient's hand function, physicians cannot provide detailed situation of hand function in daily life to patients and their family.

To overcome the aforementioned limitation, this study proposes a novel parameter for quantizing the quality of hand movement for both healthy subjects and stroke patients. This parameter was obtained by calculating the average dynamic time warping (DTW) values after 20 trials derived by comparing the finger ROM trajectory and normal pattern curves [15], [16]. The normal pattern comprised an average of 300 finger ROM trajectories obtained in the CTT from the 15 healthy subjects.

Figs. 8(a) and 8(b) present the finger ROM trajectories of the index PIP joint derived after the 20 trials for a healthy subject and a stroke patient, respectively. The finger ROM trajectories of the healthy subject were highly regular, as evidenced by the similarity of the multiple curves, thus resulting in a relatively low DTW distance. Conversely, the trajectories of the stroke patient were highly irregular, producing a large DTW distance. Therefore, the DTW distance associated with the completion of 20 executions of the CTT provided a quantitative indication of smoothness.

IV. Experimental Results

Each subject's hand function was evaluated using three features, namely the ARS, VMCT, and QM, which represent the mobility, stability, and smoothness of the subject's hand function, respectively. The Kruskal Wallis test was used to analyze the association between each feature and the BS.

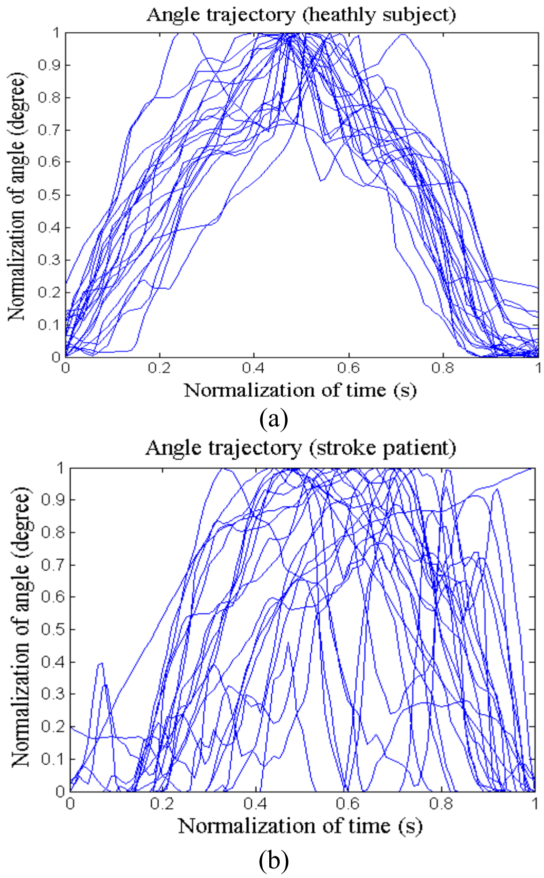

Fig. 8. Comparison of finger ROM trajectory curves: (a) healthy subjects and (b) stroke patients.

This study used 2D scatter plots and 3D scatter plots of these three features to illustrate the recovery levels and BSs of the stroke patients. The proposed system can support physicians in arranging rehabilitation treatment programs for stroke patients.

A. Mobility Evaluation

The ARS was inferred from the angular velocity of the data glove when the subject performed the GT and TT. The result in Fig. 9(a) indicates that the ARS decreased when the BS was low. The interquartile ranges (IQRs) of the BS4, BS5, and HS were 169.99, 441.34, and 507.40, respectively. The association between the ARS and BS was observed to be statistically significant ($p < 0.001$).

B. Stability Evaluation

The VMCT was observed by monitoring the time required to complete the CTT. As indicated in Fig. 9(b), the VMCT decreased when the BS was high. The IQRs of BS4, BS5, and HS were 0.79, 0.14, and 0.03, respectively. Moreover, the association between the VMCT and BS was statistically significant ($p = 0.002$).

C. Smoothness Evaluation

The QM was inferred from changes in the finger ROM when the card was turned in the CTT. As illustrated in Fig. 9(c), the QM decreased when the BS was high. The IQRs of BS4, BS5, and HS were 0.90, 0.20, and 0.18, respectively. Although the median of the QM seemed to be different at the BS, the Kruskal Wallis test revealed only a weak association between the QM and BS ($p = 0.071$).

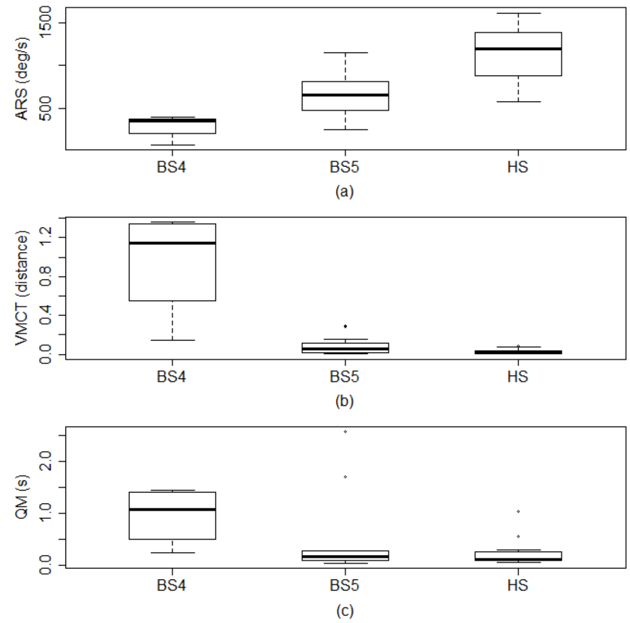

Fig. 9. Box-plots of three features for all groups: (a) ARS, (b) VMCT, and (c) QM.

D. Overall System Performance

Any two features can be used to produce a 2D scatter plot, which can provide detailed indications of hand function including mobility, stability, and smoothness. Moreover, 3D scatter plots can be used to judge the BSs of the stroke patients. Accordingly, several 2D scatter plots can be formulated, including plots of the ARS against the VMCT (A–V scatter plot), the QM against the ARS (Q–A scatter plot), and the QM against the VMCT (Q–V scatter plot).

In this study, an A–V scatter plot was created to provide indications of mobility and stability in hand function, as shown in Fig. 10(a). Because healthy people have better hand function, are more sensitive, and are able to complete tasks stably, the ARS values of the healthy subjects were higher, whereas the VMCT values were lower. The healthy subjects' points are shown in top-left corner in the figure. Because the BS can be used to present an approximation of hand function in stroke patients, if a patient's BS is low, the patient's situation is poor. Fig. 10(a) indicates a clear trend toward the bottom-right corner. Specifically, the ARS values were low and the VMCT values were high, and the corresponding BSs ranged from high to low; that is, the points of the BS4 group are distributed in the bottom-right corner of the figure, thus indicating poor mobility and stability.

A Q–A scatter plot was developed to demonstrate the correlations between smoothness and mobility in hand function. As shown in Fig. 10(b), the healthy subjects could complete

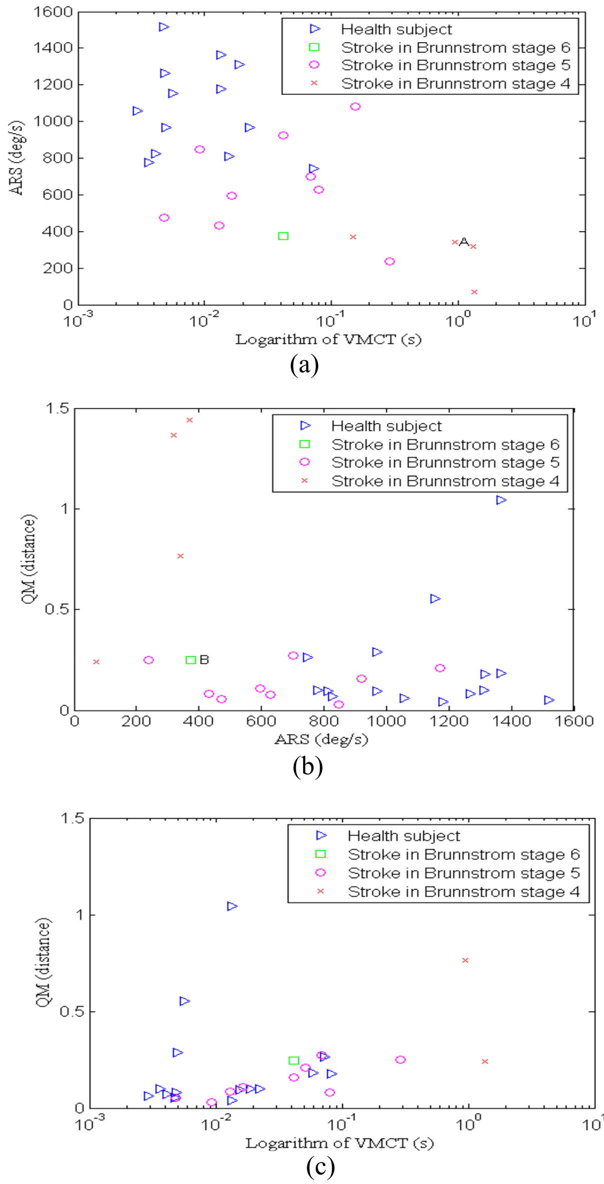

Fig. 10. Scatter plots of hand function as determined for all participants: (a) ARS versus VMCT, (b) QM versus ARS, and (c) QM versus VMCT.

the tasks precisely and rapidly. The healthy subjects had low QM values and high ARS values; the distribution is thus in the bottom-right corner of the figure. By contrast, the hand function values of the stroke patients were quantitatively poor. Specifically, the stroke patients had high QM values and low ARS values; therefore, the point distribution is close to the upper-left corner of the figure. The corresponding BSs of the patients ranged from high to low; that is, the BS4 points are distributed near the upper-left corner of the figure, thus demonstrating poor smoothness and mobility.

Finally, a Q–V scatter plot was formulated to represent smoothness and stability, as illustrated in Fig. 10(c). However, although A–V and Q–A scatter plots are mainly used for evaluation, Q–V scatter plots are not medically appealing because such plots contain few significant differences, as observed in this study. Specifically, the positions of points for BS5 and the healthy group were observed to be too close.

TABLE III
CALCULATED DISTANCE BETWEEN TS_i AND THE CENTER OF EACH GROUP

Test subject	Center of HS	Center of BS5	Center of BS4	BS
TS1	0.2605*	0.3528	1.1042	HS
TS2	0.4715	0.2568*	1.0264	BS5
TS3	1.0256	0.8677*	0.9147	BS4

* is the shortest distance between TS_i and the center of each group. i is the number of test subjects.

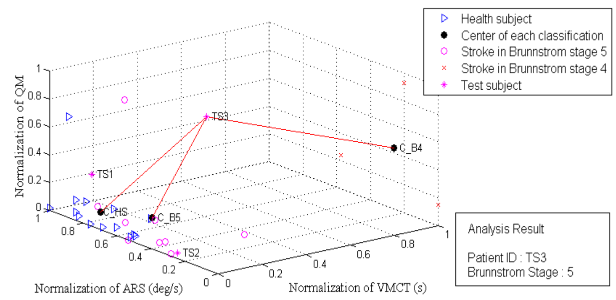

Fig. 11. Classification of participants in 3D feature space.

E. Classification and Validation

A k-means clustering algorithm was used to classify the test samples into one of the three groups [17]. The distances between each subject's point and the center of each group in the 3D feature scatter plot can be compared to determine the subject's BS. In this study, all stroke patients were classified as being in BS4–BS6, and only one stroke patient was classified as being in BS6. Thus, the proposed system can register the differences between healthy subjects and stroke patients only in BS4 and BS5.

In this study, the subjects were divided into a test group (three subjects) and a training group (the remaining subjects). As shown in Fig. 11, the three test subjects were marked as TS1, TS2, and TS3. The remaining 13 healthy subjects and 12 stroke patients were divided into the following groups: HS, BS4, and BS5. The average point coordinates were used to compute the center of each group, as indicated by the three black points C_HS, C_BS4, and C_BS5. The stars in Fig. 11 represent the three subjects of the test group. According to a doctor's diagnosis, TS1–TS3 were healthy. The points of BS5 and BS4 were associated with stroke patients. The proposed evaluation system used the shortest distance between each subject and the center of each group to determine the BS. The results are listed in TABLE III. These distance calculations can be simplified by normalizing the dimensions such that all ARS, VMCT, and QM values are between 0 and 1.

To determine the hit rate of the proposed evaluation system, k-fold cross validation was applied to verify the accuracy of the classifications. This validation process involved 2-fold, 10-fold, and leave-one-out cross validation procedures.

TABLE IV presents the results of the three cross-validation procedures: for the diagnoses provided by physicians, DHS represents healthy subjects diagnosed by a doctor, DB5 represents stroke patients classified as being in BS5, and DB4

TABLE IV
ACCURACY OF BS CLASSIFICATION BY K-FOLD CROSS VALIDATION

	2-fold cross validation			10-fold cross validation			leave-one-out cross validation		
	S_HS	S_B5	S_B4	S_HS	S_B5	S_B4	S_HS	S_B5	S_B4
DHS	80.36%	19.64%	0.00%	73.33%	26.67%	0.00%	73.33%	26.67%	0.00%
DB5	20.00%	50.00%	30.00%	30.00%	70.00%	0.00%	30.00%	60.00%	10.00%
DB4	0.00%	25.00%	75.00%	0.00%	25.00%	75.00%	0.00%	25.00%	75.00%
Hit rate	68.45%			72.78%			69.44%		

represents stroke patients classified as being in BS4; however, for the points from our data-glove-based hand function evaluation system, S_HS represents subjects diagnosed by our system as healthy, S_B5 represents stroke patients classified as being in BS5, and S_B4 represents stroke patients classified as being in BS4. The diagnoses provided by physicians helped to verify our classification results. The 2-fold, 10-fold, and leave-one-out cross validation procedures revealed comprehensive hit rates of 68.45%, 72.78%, and 68.45%, respectively. In the proposed system, the average hit rate was 70.22%, proving that this system can provide a reference to doctors regarding a patient's BS.

V. Discussion

This study derived objective parameters for evaluating the manual dexterity of stroke patients, and the findings associated with the parameters are described subsequently. Fig. 9 illustrates the distribution of the three evaluation features for each group. The ARS [Fig. 9(a)] decreased when the BS was low, implying that the HS group had the best mobility and highest ARS values. By contrast, the BS4 group exhibited the worst mobility and lowest ARS values. Therefore, the ARS can be used to discriminate the different BSs, as indicated by the statistically significant comparison results.

As shown in Fig. 9(b), when the BS was low, the stroke patients were more prone to unstable movements in the CTT, and the VMCT increased. By contrast, the median of the VMCT decreased when the subject's hand function was stable. In addition, because the hand movements of the BS4 group were usually unstable, notable differences in the VMCT values were found for each patient in this group. Therefore, the VMCT can be used to discriminate the different BSs, as signified by the statistically significant comparison results.

The overall average QM of the HS group was the lowest, and the average QM of the BS4 group was the highest [Fig. 9(c)]. This means that the hand function of the HS group was smoother than that of the BS4 group. Two of the stroke patients in the BS4 group performed the CTT slowly; their finger ROM curves were similar, and their QM values were lower than those of the healthy subjects. The observed association was statistically nonsignificant because of the close association between the BS5 and HS groups; this implies that the two groups had similar smoothness levels in terms of hand function.

In this study, A–V and Q–A scatter plots were used to evaluate the distributions between the patients in BS4 and BS5 and healthy subjects. In Fig. 10(a), point A in the A–V scatter plot represents the data of a patient classified in the BS4 group. For such patients, physicians would be recommended to modify the rehabilitation treatment to enhance stability training tasks. However, there were no significant differences between the HS, BS5, and BS6 groups. The VMCT comparison also yielded nonsignificant results, except for the BS4 group. These results show that the stroke patients classified in the BS5 and BS6 groups performed each CTT stably, in a manner similar to that of healthy people. However, the distribution of the ARS in each group was wider because the hand movements of stroke patients were slower than those of the healthy subjects. Therefore, for such patients, the system would recommend physicians to increase the mobility rehabilitation exercises and to monitor the patients' levels of progress. In Fig. 10(b), point B in the Q–A scatter plot represents the data of a patient classified in the BS6 group. For such patients, physicians would be recommended to enhance the patients' mobility. If the subject was improving the mobility, the results would resemble those of the HS group. Therefore, the proposed system can provide therapists with 2D feature scatter plots that can support their medical decisions regarding rehabilitation.

The classification of the BS is discussed in Section IV-D. The present study used the distance between the subject and center of each group to execute the classification. For example, in Fig. 11, TS1, TS2, and TS3 represent test subjects, and the Euclidean distance was used to compute the distance between each subject and the center of each group. Each subject was classified into the group located at the shortest distance from the subject. In TABLE III, the distance between the subject and the center of each group provides the BS. TS1 and TS2 were classified correctly, but TS3 was classified incorrectly. The distances between TS3 and the centers of the HS group, BS5 group, and BS4 group were d_1, d_2, and d_3, respectively. TABLE III indicates that the relation of d_1, d_2, and d_3 is $d_2 < d_3 < d_1$. This result reveals that although TS3 was classified as being in BS4 by therapists, the features of this subject's manual dexterity are close to those of the patients in the BS5 group. This implies that TS3 can be defined as a patient falling between BS4 and BS5, but closer to BS5. This is one of the detailed information items that cannot be observed by therapists.

TABLE IV shows the validation results regarding the hit rates in the BS classification. The 2-fold cross-validation procedure revealed the lowest hit rate (68.48%). The 2-fold cross-validation procedure entailed dividing all the subjects into two sets (D_0 and D_1). In the first cross validation, D_0 served as the training set, whereas D_1 served as the test set;

TABLE V
COMPARISON BETWEEN THE PROPOSED SYSTEM AND OTHER SYSTEMS

System	S. Allin *et al.* [4]	Yu *et al.* [8]	C. Strohrmann *et al.* [18]	Proposed System
Sensor	Camera	Flex Sensor	ETH orientation sensor (ETHOS)	IMU
Data	Hand velocity, elbow angle	Angle	Acceleration, angular velocity	Acceleration, angular velocity, angle
Portable	No	Yes	Yes	Yes
Modular design	No	No	No	Yes
Grading	No	Yes	No	Yes
Hand function assessment	No	Yes	No	Yes
Transmission interface	USB	ZigBee	Store in microSD	Bluetooth
Applications	Assess stroke's limb function performance	Calculate finger joint angle and assess stroke's limb and hand function	Assess stroke's motor performance in daily life	Assess stroke's hand function performance and Brunnstrom stage classification

the hit rate of D_1 was calculated. After the derivation of the hit rate of D_1, D_1 was swapped with D_0 for the next validation.

The overall hit rate in the 2-fold cross-validation procedure was derived as the average of the results of the two validations. In this case, the hit rate was not precise because of insufficient training data. Furthermore, because the data of the BS5 group were widely distributed, some data of this group were closer to the HS group than to the BS4 group. Thus, for some patients, our system provided diagnoses that differed from the diagnoses of physicians. This study therefore applied a 10-fold cross-validation procedure to validate the hit rate; this procedure revealed a hit rate of 72.78%. Hence, for this study, the 10-fold cross-validation procedure effectively classified all subjects.

The present study has some limitations that must be resolved in the future. First, a finger's ROM cannot be measured in the horizontal plane because the inertial sensors on the data glove include accelerometers and gyroscopes, but not magnetometers. Without magnetometers, numerous errors accumulate in the horizontal plane. Therefore, this data glove cannot be used to evaluate complicated tasks in patients' daily lives, such as turning keys or writing. In the future, a more effective algorithm must be developed to measure a finger's ROM in 3D space; such an algorithm can evaluate more complicated finger movements. Second, the number of subjects participating in this study was excessively low. In the future, a higher number of subjects must be recruited for clinical experiments to validate the performance of the system. Third, the data segmentation procedure in this study was only partially automated. A fully automated algorithm must be implemented to simplify the data segmentation procedure and explore more parameters of 3D actions.

TABLE V presents comparisons between the proposed system and systems implemented in related research. Strohrmann *et al.* [18] proposed a body movement evaluation system for children who had suffered strokes and for cerebral palsy patients. In this system, ETH orientation sensors measure acceleration and angular velocity to monitor the movements of children, and the data are saved in SD cards. The extracted features are very similar to the features of our system. However, because most of the features are from large joints, they cannot be used to evaluate the small joints involved in finger or hand function. Only two stroke patients and two cerebral palsy patients were described in the previous study; therefore, obtaining a reliable evaluation result would necessitate the use of a larger patient population. Allin *et al.* [4] proposed an arm joint capturing system for stroke patients; this system uses six cameras. However, cameras are marred by serious environmental restrictions and shielding problems. Furthermore, both of the described studies monitored only body joints. Detailed hand function was unobservable, and observations may be limited because of environmental constraints. In 2016, Yu *et al.* [8] used a data glove with flex sensors to measure hand joints in stroke patients; the data glove overcomes the problem of environmental restrictions and measures the hand and finger movements in detail. However, the resistive sensors used in that data glove cannot measure the real accelerations and angular velocities of finger movements. That data glove is not an integrated unit, and if it is broken, the required repair would be expensive and inconvenient.

Most previous studies could not propose a convenient wearable monitoring device that can assess hand function and support physicians in the classification of stroke patient levels. To address such problems, the current study proposes a data glove system integrating with six-axis IMU sensors for hand function evaluation. A Bluetooth interface is used to transmit data wirelessly and increase the convenience of experimental tasks. Our modular design can be customized to fit each patient's unique hand anatomy, and the system can calculate the acceleration, angular velocity, and finger ROM to evaluate a stroke patient's hand function and classify the patient's BS. This system can also provide therapists with effective information regarding a patient's hand function; such information can support medical diagnosis and rehabilitation arrangements.

VI. CONCLUSION

This study proposes a data glove system combined with six-axis IMU sensors for hand function evaluation. This modular system can be adjusted so that it can be worn by patients with various hand characteristics. This system uses sensors covering a stroke patient's hand to monitor the patient's hand function. A clinical experiment was conducted by recording participants' hand function features as they performed various tasks. The system classified and analyzed the BSs patients. This system provided quantitative data and 2D scatter plots of relevance to medical treatments. By means of 3D feature scatter plots, distances were compared to determine the BSs of the patients. The classification was validated through k-fold cross validation, and the average hit rate was 70.22%. The proposed system can provide therapists with reliable information regarding patients' BSs.

Because only 15 healthy subjects and 15 stroke patients participated in the experiment, the experimental data showed deviation in the assessment results and classification hit rates. Future clinical experiments must include higher numbers of stroke patients classified in different BSs to increase the reliability and classification hit rates of the system.

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