An Assessment System for Post-Stroke Manual Dexterity Using Principal Component Analysis and Logistic Regression
使用主成分分析和 logit 模型的卒中后手动灵活性评估系统

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***Abstract* — Hand function assessment is crucial for patients with stroke, who must perform regular repeti-tive tasks during rehabilitation. However, the conventional evaluation method is subjective and not uniform among physicians. A novel method is proposed in this paper to analyze raw data from a data glove equipped with 16 six-axis inertial measurement units. The proposed method can provide accurate assistance to physicians and objectively assess patients' hand function. Three tasks (the thumb task, the grip task, and the card-turning task) were conducted to evaluate participants' hand function. Representative para-meters of hand function in each task and overall evaluation were extracted through principal component analysis and used to develop logistic regression models. The results revealed that all three tasks can be used to perfectly predict healthy subjects and subjects with stroke, with the thumb task exhibiting the highest predictive accuracy for the sever-ity of hand dysfunction. Overall, the proposed method can serve as an efficient method for physicians to assess the hand function of patients with stroke.**

摘要一手功能评估对中风患者至关重要，他们必须在康复期间执行定期重复的任务。然而，传统的评估方法是主观的，在医生中并不统一。本文提出了一种新的方法来分析来自装备有 16 个六轴惯性测量单元的数据手套的原始数据。所提出的方法可以为医生提供准确的帮助，客观地评估患者的手功能。进行三项任务(拇指任务，握把任务和翻卡任务)来评估参与者的手功能。采用主成分分析法提取各任务中手功能的代表性参数，并进行综合评价，建立 logistic 回归模型。结果表明，三种任务均能较好地预测健康受试者和脑卒中受试者的手功能障碍程度，其中拇指任务对手功能障碍程度的预测准确性最高。总体而言，所提出的方法可以作为医生评估中风患者手功能的有效方法。

***Index Terms*— Data glove, hand function evaluation, logistic regression, principal component analysis, stroke.**
数据手套，手功能评估，logit 模型，主成分分析，脑卒中。

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I. Introduction
引言

STROKE is the primary cause of hand function impair-ment. From 2003 to 2013, approximately 795 000 people experienced strokes (for the first time or recurrent strokes) [1].
卒中是手功能损害的主要原因。从 2003 年到 2013 年，大约 795000 人经历了中风(第一次或复发性中风)[1]。

Patients with stroke and hand function impairment require reg-ular rehabilitation to recover. Meanwhile, physicians regularly observe the hand function of such patients to assess their hand function ability and modify recovery plans based on patients' hand function ability.
中风和手功能障碍患者需要定期康复以恢复。同时，医生定期观察这些患者的手功能，以评估他们的手功能能力，并根据患者的手功能能力修改恢复计划。

A physician uses conventional functional scales to assess the quality of a patient's movement when the patient performs repetitive movement tasks. Brunnstrom stages (BSs), which use six levels to represent the condition of a patient's hand function, are one of the most common clinical methods for assessing the severity of hand impairment [2]. Although conventional scales are widely used, they are subjective and are not uniform among physicians. The ceiling effect can occur as a result of limited scales, which can affect a physi-cian's diagnosis. Thus, measurement errors can occur when a patient's condition is between two BSs. Therefore, an objective and accurate quantitative assessment method is required to overcome the limitations of conventional scales.

当病人执行重复性运动任务时，医生使用传统的功能量表来评估病人的运动质量。Brunnstrom 分期(BSs)是评估手部损伤严重程度的最常用的临床方法之一，它使用六个水平来代表患者的手部功能状况。虽然传统的量表被广泛使用，但它们是主观的，在医生中并不统一。由于规模有限，可能会影响医生的诊断，上限效应可能会发生。因此，当患者的病情介于两个 BSs 之间时，测量误差可能会发生。因此，需要客观和准确的定量评估方法来克服传统量表的局限性。

Many quantitative assessment methods involving the use of customized tools for the upper limbs and hands of patients with stroke have been proposed. In 2014, Lee *et al.* proposed a smartphone-centric system to measure the range of motion and evaluate the joint condition of patients with stroke [3]. In 2016, Venkataraman *et al.* proposed a camera-based system to extract crucial features from the motion data of patients with stroke and predict movement quality scores [4]. These studies have provided quantitative methods to accurately evaluate the range of motion and quality of movement; however, these methods are suitable only for wide-joint measurement, which means they are unsuitable for finger-joint assessment.

已经提出了许多涉及使用定制工具对中风患者的上肢和手进行定量评估的方法。2014 年，Lee 等人提出了一个以智能手机为中心的系统来测量中风患者的运动范围和评估关节状况[3]。2016 年，Venkataraman 等人提出了一个基于摄像机的系统，从中风患者的运动数据中提取关键特征，并预测运动质量评分[4]。这些研究为准确评价运动范围和运动质量提供了定量方法，但这些方法仅适用于宽关节测量，不适用于指关节测量。

Several studies have used various tools to quantify finger movement quality. Most of these studies have focused on finger movement quality for Parkinson's disease [5]–[8], and they have quantified finger condition by extracting related features when patients with Parkinson's disease perform finger tapping or other evaluation tasks. These studies have pro-vided complete and valuable quantification methods to assess patients' finger conditions. However, these methods are only applicable to Parkinson's disease symptoms. Several studies have provided customized tools or methods to quantify finger movement quality. In 2015, Térémetz *et al.* developed a finger force manipulandum to measure the power of the index,

一些研究使用各种工具来量化手指运动的质量。这些研究大多集中在帕金森病的手指运动质量[5]-[8]，他们通过提取帕金森病患者进行手指敲击或其他评估任务时的相关特征来量化手指状况。这些研究提供了完整和有价值的量化方法来评估患者的手指状况。然而，这些方法仅适用于帕金森病症状。几项研究提供了定制的工具或方法来量化手指运动质量。2015 年，Térémetz 等人开发了一种手指力操纵器来测量指数的力量，

middle, ring, and little fingers [9]. However, measuring only finger power is inadequate for hand function quantification. With advancements in technology, several sensors have been developed and applied in the rehabilitation domain. Data gloves consisting of various types of sensors have been proposed to evaluate the hand function of patients with stroke. In 2014, Kortier *et al.* developed a sensor glove equipped with inertial measurement units (IMUs) to accurately quantify finger-joint condition [10]. In 2016, Zheng *et al.* presented
中指，无名指和小指[9]。然而，仅测量手指功率不足以量化手功能。随着技术的进步，几种传感器已经开发并应用于康复领域。已经提出了由各种类型的传感器组成的数据手套来评估中风患者的手功能。2014 年，Kortier 等人开发了一种装有惯性测量单元(IMUs)的传感器手套，以准确量化手指关节状态[10]。2016 年，Zheng 等人提出
a data glove equipped with bend sensors and force-sensing resistors to measure joint angles and finger pressure [11]. These two studies have demonstrated the reliability of their respective systems; however, they have focused on verifying system reliability but have not provided quantitative methods or revealed specific features of hand function. In 2012, Oess *et al.* proposed a sensor glove that consisted of flex sensors using quantitative methods to assess the hand function of patients with stroke [12]. In 2016, Yu *et al.* proposed a remote quantitative Fugl–Meyer assessment framework for such patients [13]; this framework extracted five types of features from each sensor and predicted Fugl–Meyer scores. These studies proposed novel methods to quantify the hand function of patients with stroke; however, both studies only used finger-joint angles for assessment and did not provide any parameters to represent detailed information regarding the hand function of patients with stroke. In 2017, Lin *et al.* proposed a data glove equipped with six-axis IMU sensors to assess the hand function of patients with stroke. Three parameters—ARS, VMCT, and QM—were extracted, and k-means was applied to classify patients' BSs [14]. Although this system can classify patients' BSs, it uses only a few motion parameters and may ignore crucial information.
装有弯曲传感器和力敏感电阻的数据手套，用于测量关节角度和手指压力[11]。这两项研究证明了各自系统的可靠性，但是，它们侧重于验证系统的可靠性，但没有提供定量的方法或揭示手功能的具体特征。2012 年，Oess 等人提出了一种传感器手套，其中包括使用定量方法评估中风患者手功能的弯曲传感器[12]。2016 年，Yu 等人为这类患者提出了一个远程定量 Fugl-Meyer 评估框架[13]；该框架从每个传感器中提取五种类型的特征并预测 Fugl-Meyer 评分。这些研究提出了量化脑卒中患者手功能的新方法，然而，两项研究都只使用手指关节角度进行评估，并没有提供任何参数来代表有关脑卒中患者手功能的详细信息。2017 年，Lin 等人提出了一种配备六轴 IMU 传感器的数据手套来评估中风患者的手功能。提取三个参数 ars，VMCT 和 qm，并应用 k 均值对患者的 BSs 进行分类[14]。尽管该系统可以对患者的 BSs 进行分类，但它只使用少数运动参数，并且可能忽略关键信息。

This study developed a method to analyze raw data from a data glove equipped with six-axis IMUs and extracted representative parameters of hand dexterity from three self-defined tasks to evaluate the hand function of patients with stroke. Compared with the previous study [14], the new approach has two main advantages. First, in the previous method, three parameters are extracted by observing the characteristics of each task's signal. However, using only three parameters to represent the performance of manual dexterity is insufficient and may lead to information loss. Therefore, a robust approach based on statistical theory was adopted in the present study to extract and select all possible parameters from each task. Second, in the previous approach, only three parameters are proposed to perform clustering. By contrast, in addition to considering all possible parameters, the present study involves more criteria, including the most influential sensor positions and tasks. Thus, physicians can assess each patient's manual dexterity efficiently in future research by adopting the key criteria presented in this paper.
本研究建立了一种分析装有六轴 IMUs 的数据手套原始数据的方法，并从三个自定义任务中提取手灵活度的代表性参数，以评价脑卒中患者的手功能。与以前的研究[14]相比，新方法有两个主要优势。首先，在前一种方法中，通过观察每个任务信号的特征来提取三个参数。然而，仅仅使用三个参数来表示手的灵活性是不够的，可能会导致信息丢失。因此，本研究采用了基于统计理论的稳健方法，从每个任务中提取和选择所有可能的参数。其次，在以前的方法中，只提出了三个参数来执行聚类。相比之下，除了考虑所有可能的参数之外，本研究还涉及更多的标准，包括最有影响力的传感器位置和任务。因此，医生可以通过采用本文提出的关键标准，在未来的研究中有效地评估每个患者的手动灵活性。

II. Method
方法

A. Participants
A. 参与者

In this study, 15 patients with stroke ("SPs" hereafter; nine male patients and six female patients, mean age: 59.3 ± 16.3 years), comprising four SPs in the fourth BS (BS4), ten SPs
脑卒中患者 15 例，男 9 例，女 6 例，平均年龄 59.3 ± 16.3 岁

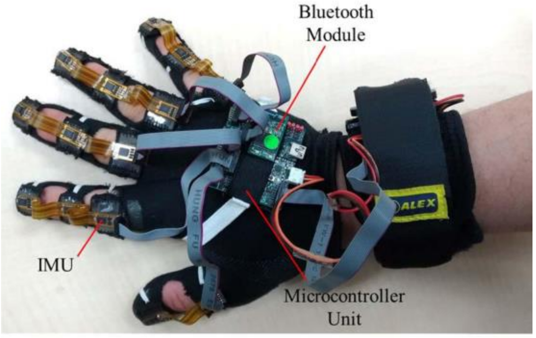


Fig. 1. Photograph of the data glove.
图 1。数据手套的照片。

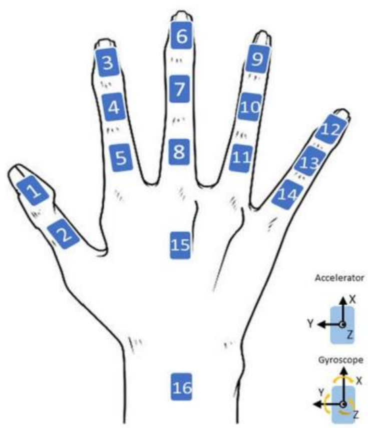


Fig. 2. Positions of the IMU sensors.
图 2。 IMU 传感器的位置。

in the fifth BS (BS5), and one SP in the sixth BS (BS6), and 15 healthy elderly individuals ("HSs" hereafter; five male individuals and ten female individuals, mean age: 62.6 ± 12.6 years) were recruited. The age difference between the SPs and HSs was nonsignificant (p = 0.3648). The experiment was conducted at Chi-Mei Hospital, Tainan, Taiwan. This research (involving human subjects) was reviewed and approved by the ethics committee of Chi-Mei Hospital (IRB No. 10102-019), and the human participants provided their informed consent.
方法: 选择健康老年人 15 例，男 5 例，女 10 例，平均年龄 62.6 ± 12.6 岁。SPs 和 HSs 之间的年龄差异不显着(p = 0.3648)。该实验在台湾台南市 Chi-Mei 医院进行。本研究由芝麻医院伦理委员会(IRB no. 10102-019)审核及批准，并由参与者提供知情同意书。

B. Data Glove
B. 数据手套

Participants were asked to wear self-developed data gloves to detect their hands' motion when performing various tasks. Each data glove consisted of 16 IMUs (LSM330DLC, STMicroelectronics, Geneva, Switzerland), and each IMU consisted of a gyroscope and an accelerometer to output three-axis angular velocities and accelerations. A microcontroller unit (MSP430, Texas Instruments Inc., Dallas, TX, USA) was used to collect data from the IMUs and wirelessly transmit the encapsulated packet to a laptop through a Bluetooth interface. Fig. 1 shows a photograph of the data glove, the mechanical design of which was detailed in our previous report [14]. Fig. 2 depicts the positions of the IMU sensors.

参与者被要求戴上自制的数据手套，以检测他们的手在执行各种任务时的动作。每个数据手套由 16 个 IMUs (LSM330DLC，意法半导体，瑞士日内瓦)组成，每个 IMU 由一个陀螺仪和一个加速度计组成，输出三轴角速度和加速度。一个微控制器单元(MSP430， Texas Instruments inc.， Dallas，TX，USA)用于从 IMUs 收集数据，并通过蓝牙接口将封装好的数据包无线传输到笔记本电脑。图 1 显示了数据手套的照片，其机械设计在我们以前的报告中详细描述[14]。图 2 描绘了 IMU 传感器的位置。

C. Experimental Tasks
C. 实验性任务

All participants were asked to perform the following three tasks, namely a thumb task (TT), grip task (GT), and

所有参与者被要求执行以下三项任务，即拇指任务(TT)，握力任务(GT)和

TABLE I
表一
EXPERIMENTAL PROCESS
实验过程

Task	Actions	Duration (s)	Cycles
Thumb task (TT)	Press the button Release the button	4 4	10
Grip task (GT)	Grip the tool Release the tool	4 4	10
(CTT)	Turn the card and place it on the table		20

Fig. 3. Cylindrical tool for the TT.
图 3.TT 用圆柱形刀具。

card-turning task (CTT), which were conducted to evaluate finger and wrist movement quality. Moreover, several scale assessments were conducted by a physician in advance on the SPs to determine their BSs to compare with the evaluation from our proposed system. Table I presents the entire process of the experiments. A detailed description of the experiments is provided in the following section.

卡片转向任务(CTT)，进行评估手指和手腕运动质量。此外，医生事先对 SPs 进行了几次量表评估，以确定他们的 BSs 与我们提出的系统的评估进行比较。表 i 列出了整个实验过程。以下部分提供了实验的详细描述。

D. Clinical Measurements
D. 临床测量

Physicians graded the hand function of the SPs on the basis of their BSs. One SP was graded as BS6, ten SPs were graded as BS5, and four SPs were graded as BS4. Because SPs with BS6 usually have similar hand function to HSs, the SP with BS6 was categorized as an HS for analysis.

医生根据他们的 BSs 对 SPs 的手功能进行分级。一个 SP 分级为 BS6，十个 SP 分级为 BS5，四个 SP 分级为 BS4。由于具有 bs6 的 SP 通常具有与 HSs 相似的手功能，因此具有 bs6 的 SP 被归类为用于分析的 HS。

1) TT: The TT was conducted to assess the participants' thumb dexterity. Each participant held a cylinder and repeat-edly pushed a button on the cylinder by using their thumb. Fig. 3 displays the cylindrical tool. In the TT, a sound alerted the participant every 4 s to perform the task. One complete motion included pressing and releasing actions. An entire task included ten repetitions of a complete motion and lasted approximately 2 min.

TT: TT 用于评估参与者的拇指灵活性。每个参与者拿着一个圆柱体，用拇指重复按下圆柱体上的按钮。图 3 显示了圆柱形工具。在 TT 中，每 4 秒钟就有一个声音提醒参与者执行任务。一个完整的动作包括按压和释放动作。整个任务包括 10 次重复一个完整的动作，持续约 2 分钟。

2) GT: The GT was a repetitive finger extension-flexion motion task, which was conducted to evaluate the participants' entire hand dexterity, especially that of the index, middle, ring, little fingers, and wrist. Each participant repetitively performed a grip and release motion by using the tool depicted in Fig. 4. Similar to the procedure in the TT, a sound alerted the participants every 4 s. A complete motion included gripping and releasing; each complete motion was repeated ten times and lasted approximately 2 min, similar to the TT.

GT: GT 是一个重复性的手指伸屈运动任务，用于评价参与者的整个手的灵活性，尤其是食指、中指、无名指、小指和腕部的灵活性。每个参与者通过使用图 4 所示的工具重复执行握力和释放动作。与 TT 中的程序类似，每 4 秒钟就有一个声音提醒参与者。一个完整的动作包括抓握和释放；每个完整的动作重复 10 次，持续大约 2 分钟，类似于 TT。

3) CTT: The CTT involved repetitive turning of a card to
CTT: CTT 包括重复翻转一张卡片到

assess the participants' hand mobility and stability. The size of the card used in the task was 7.62 × 12.70 cm ^{2}, as displayed

评估参与者的手部活动性和稳定性。如图所示，任务中使用的卡片大小为 7.62 ×12.70 cm 2

Fig. 4. Tool for the GT.
图 4 燃气轮机用工具。

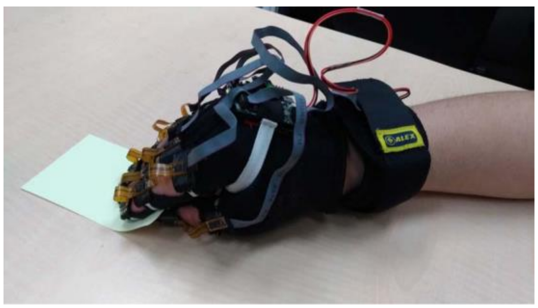


Fig. 5. Card for the CTT.
图 5。 CTT 卡。

in Fig. 5. Each participant turned the card 20 times and carefully placed the card to ensure completion of the entire action. The goal of this task was to compare the hand mobility and stability of SPs with those of HSs. The entire motion was repeated 20 times, and the participants were instructed to turn the card as quickly as possible.

图 5。每个参与者转动卡片 20 次，并小心地放置卡片，以确保完成整个动作。这个任务的目标是比较 SPs 和 HSs 的手的移动性和稳定性。整个动作重复了 20 次，并指示参与者尽快转动卡片。

E. Data Analysis
E. 数据分析

In the previous method [14], three parameters, namely ARS, VMCT, and QM, are extracted by observing the characteristics when the SPs and HSs perform the three tasks. However, only the clustering method is used to present the distribution of subjects according to the three parameters. This means that the aforementioned method can only show the clusters using the extracted three features and cannot guarantee the stability and accuracy of assessing the subjects' manual dexterity. Therefore, in the present study, a more robust statistics-based data analysis method was adopted to explore all possible parameters and select the most critical features from the raw data obtained from all IMUs and all tasks. After obtaining all possible significant features, a stable model for manual dexter-ity assessment could be created using logistic regression (LR).

在前一种方法[14]中，通过观察 SPs 和 HSs 执行这三个任务时的特征，提取了 ARS、 VMCT 和 QM 三个参数。然而，只有聚类方法被用来根据三个参数呈现主题的分布。这意味着上述方法只能利用提取的三个特征来显示聚类，不能保证评估被试人手灵巧度的稳定性和准确性。因此，本研究采用了一种更稳健的基于统计的数据分析方法，以探索所有可能的参数，并从所有 IMUs 和所有任务获得的原始数据中选择最关键的特征。在获得所有可能的显著特征后，可以利用逻辑回归(LR)方法建立一个稳定的人工右侧功能评估 logit 模型。

SAS 9.4 (SAS Institute Inc., Cary, NC, USA) was used to conduct data analysis. Based on the participants' conditions, each participant repeated each task two to five times. Most of the participants repeated the CTT three times. Overall, 111 task recordings were obtained from the HSs and 107 task recordings were obtained from the SPs. In this experiment, 88, 66, and 64 task recordings were obtained from the CTT, GT, and TT, respectively. Data analysis was divided into two parts. The first part classified the HSs and SPs. The data analysis procedure for the first part is presented in Fig. 6. The procedure

使用 SAS 9.4(SAS Institute inc. , Cary, NC, USA)进行数据分析。根据参与者的条件，每个参与者重复每个任务两到五次。大多数参与者重复了三次 CTT。总体而言，从 HSs 获得了 111 个任务记录，从 sp 获得了 107 个任务记录。在这个实验中，分别从 CTT，GT 和 TT 获得 88,66 和 64 个任务记录。数据分析分为两部分。第一部分对 HSs 和 SPs 进行了分类。第一部分的数据分析过程如图 6 所示。程序

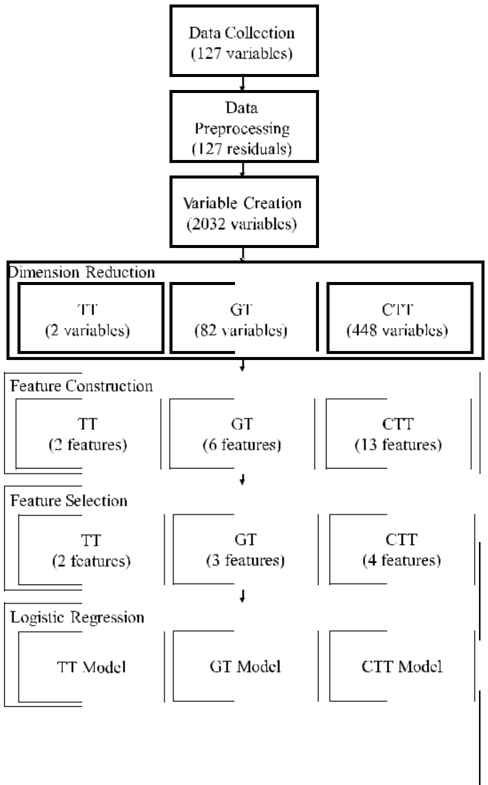


Fig. 6. Data analysis procedure of classifying HSs and SPs.
图 6。分类 HSs 和 SPs 的数据分析程序。

included data collection, data preprocessing, variable creation, dimension reduction, feature construction, feature selection, and LR [15].
包括数据采集、数据预处理、变量创建、维度减化、特征构造、特征选择和 LR [15]。

The second part verified whether the constructed features could be used to classify the severity of the subjects. The Kruskal–Wallis test was used to differentiate severity among features constructed from the feature construction process in the first part.
第二部分验证了构建的特征是否可以用于对受试者的严重程度进行分类。在第一部分中，使用 Kruskal-Wallis 检验来区分从特征构建过程构建的特征的严重性。

1) Data Collection: For data collection, 16 IMU sensors were placed on each participant’s hand. The acceleration of each sensor was recorded for three directions; thus, 48 acceleration variables were obtained. The change in the total acceleration, which was defined as the square root of the sum of squared acceleration for each direction, was calculated for each sensor, thereby, providing 16 variables. Similarly, for each sensor, the angular velocities were calculated for all three directions. Therefore, 48 angular velocity variables were collected. Every two adjacent sensors incorporated an included angle; thus, the 16 sensors produced a total of 15 angles of finger joints. Overall, 127 variables were collected from each participant.
数据收集: 为了数据收集，16 个 IMU 传感器被放置在每个参与者的手上。记录每个传感器的加速度的三个方向; 因此，获得了 48 个加速度变量。总加速度的变化被定义为每个方向加速度

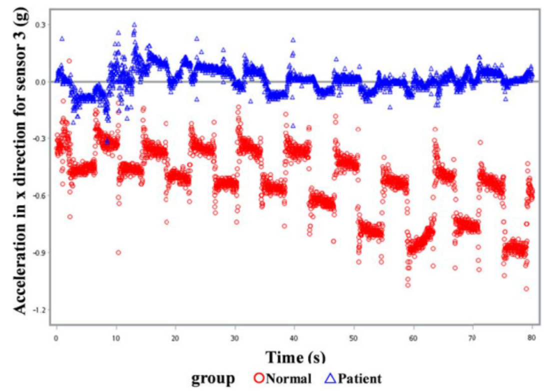


Fig. 7. Acceleration over time in the x-direction for the third IMU sensor during the TT as an example of an upward and downward trend.
图 7。在 TT 期间，第三个 IMU 传感器随着时间的推移在 x 方向上加速，作为一个上升和下降趋势的例子。

平方和的平方根，对每个传感器进行了计算，从而提供了 16 个变量。同样，对于每个传感器，计算所有三个方向的角速度。因此，收集了 48 个角速度变量。每两个相邻的传感器都包含一个包含的角度; 因此，16 个传感器总共产生了 15 个指关节的角度。总体而言，从每个参与者收集了 127 个变量。

2) Data Preprocessing and Variable Creation: An upward or downward trend was possible for each variable, as indicated in Fig. 7. A simple linear regression model was used to determine the systematic trend. The estimated intercept and slope were computed for each variable, and the residuals that determined the systematic trend were computed. Four summary statistics, namely the mean, median, standard deviation, and interquartile range for the residuals, were computed for each cycle. Overall, 508 variables were obtained from each participant. Subse-quently, the average values (mean and median) of these sum-mary statistics for only the intermediate cycles were computed; the computation yielded 1016 variables. Using these variables
数据预处理和变量创建: 如图 7 所示，每个变量都可能有上升或下降的趋势。使用简单线性回归模型来确定系统趋势。计算每个变量的估计截距和斜率，并计算确定系统趋势的残差。四个总结统计，即平均值，中位数，标准差，和四分差范围的残差，计算了每个周期。总体而言，从每个参与者获得 508 个变量。同时，只计算中间周期的这些总和统计量的平均值(平均值和中位数)，计算得到 1016 个变量。使用这些变量

calculated from mean and median, the average location and average variation per cycle were obtained. Furthermore, variabilities (standard deviation and interquartile) of the mean and median values of the intermediate cycles were computed; the computation provided 1016 variables. Overall, each task consisted of 2032 variables.
根据平均值和中位数计算，得到每个周期的平均位置和平均变化量。此外，还计算了中间循环的平均值和中间值的变异能力(标准差和四分位数)，计算结果提供了 1016 个变量。总体而言，每个任务由 2032 个变量组成。

3) Dimension Reduction and Feature Construction: Because each task consisted of 2032 variables, a two-independent-sample t-test was conducted to identify the most crucial variables. A total of 448 and 82 variables of the CTT and GT, respectively, exhibited significant differences in a comparison of the two groups (HSs and SPs). However, for the TT, only two variables that measured the variability of angular velocity in the y-direction from sensor 1 exhibited significant differences in a comparison of the two groups. For the CTT, 57.8% of variables were obtained from angular velocity,

维度减化和特征构建: 由于每个任务由 2032 个变量组成，因此采用双独立样本 t 检验来确定最关键的变量。CTT 和 GT 分别有 448 个变量和 82 个变量，两组比较差异有显著性(HSs 和 SPs)。然而，对于 TT 来说，只有两个变量测量了来自传感器 1 的 y 方向的角速度的变化，在两组的比较中显示出显著的差异。对于 CTT，57.8% 的变量来自角速度,

22.3% of variables were obtained from acceleration, 6.9% of variables were obtained from the amount of change of the total acceleration, and 4% of variables were obtained from the joint angles. For the GT, 67.4% of variables were constructed from angular velocity, 18.6% of variables were calculated from acceleration, 7% of variables were obtained from the amount of change of the total acceleration, and 7% of variables were constructed from the joint angles.
22.3% 的变量来源于加速度，6.9% 的变量来源于总加速度的变化量，4% 的变量来源于关节角度。对于 GT，67.4% 的变量是由角速度构成的，18.6% 的变量是由加速度计算的，7% 的变量是由总加速度的变化量得到的，7% 的变量是由关节角构成的。

Because the variables were highly correlated, principal component analysis (PCA) was employed to construct the features. The number of variables was considerably higher than the number of participants. Before constructing the principal components, a heat map for the correlation of variables, as shown in Fig. 8, was created for identifying the highly correlated variables. Based on the heat map, 13 groups of variables were identified for the CTT, and six groups of variables were identified for the GT. For the CTT, two groups of variables were related to the location and 11 groups of variables were related to the variability of the location. By contrast, for the GT, all six groups of variables were related to the variability.

由于变量高度相关，因此采用主成分分析(PCA)构建特征。变量的数量远远高于参与者的数量。在构造主成分之前，为变量的相关性创建了一个热图，如图 8 所示，用于识别高度相关的变量。基于热图，确定了 CTT 的 13 组变量，并确定了 GT 的 6 组变量。对于 CTT，两组变量与位置有关，11 组变量与位置的变异性有关。相比之下，对于 GT，所有六组变量都与变异性有关。

PCA was then used in each group of variables to construct specific features for the CTT and GT. All extracted components are listed in the appendix. Variables extracted from the CTT were classified into 13 groups. The first group included eight variables, which were obtained from the mean of the

然后在每组变量中使用 PCA 来构造 CTT 和 GT 的特征。所有提取的组分都列在附录中。从 CTT 中提取的变量被分为 13 组。第一组包括八个变量，这些变量是从

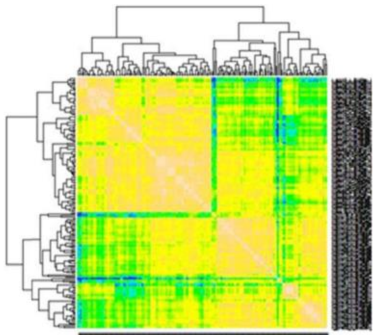


Fig. 8. Heat map based on the correlation of the 530 significant variables in the CTT and GT. 13 groups of variables were identified for the CTT and 6 groups of variables were identified for the GT.
图 8。基于 CTT 和 GT 中 530 个重要变量的相关性的热图。为 CTT 确定了 13 组变量，为 GT 确定了 6 组变量。

standard deviation per cycle of acceleration in the x-direction of sensors 3, 4, 6, 7, 9, 10, 12, and 13. The component extracted from this group exhibited 98% variance and was named as feature *A*. The second group included 20 variables, which were obtained from the mean of the standard deviation per cycle of acceleration and the amount of change in the total acceleration in the x- and z-directions. In addition to the sensors in feature *A*, the second group included sensors 5 and
传感器 3、4、6、7、9、10、12 和 13 的 x 方向上每个加速周期的标准差。从该组中提取的组分表现出 98% 的方差，并被命名为特征 a。第二组包括 20 个变量，这些变量是从每个加速度周期的标准差的平均值和总加速度在 x 和 z 方向的变化量中得到的。除了特征 a 中的传感器之外，第二组包括传感器 5 和

11. This group extracted one component, which exhibited
这个小组提取了一个组件，展示了

96.7% variance and was named feature *B*. The third group included 12 variables obtained from the mean of the interquar-tile per cycle of acceleration in the x-direction. The component extracted from this group exhibited 96.8% variance. The component contained all the variables from sensors 3 to 14 and was named feature *C*. The fourth group included 15 variables obtained from the mean of the standard deviation per cycle of acceleration in the y- and z-directions. This component used all the variables from sensors 3 to 14, except sensor 9. This group extracted one component, which exhibited 97.8% variance and was named feature *D*. The fifth group included
方差为 7%，命名为特征 b。第三组包括从 x 方向每个加速周期的四分位间距的平均值获得的 12 个变量。从该组提取的组分表现出 96.8% 的方差。该组件包含从传感器 3 到 14 的所有变量，并被命名为特征 c。第四组包括 15 个变量，它们来自 y 和 z 方向上每个加速度周期的标准差的平均值。该组件使用了传感器 3 至 14 的所有变量，除了传感器 9。该组提取了一个组件，其表现出 97.8% 的方差，被命名为特征 d。第五组包括

27 variables obtained from the mean of the interquartile per cycle of acceleration and the total acceleration in the x-, y-, and z-directions depending on the location of the sensors. This group extracted one component, which exhibited 95.4% variance and was named feature *E*. The sixth group included
根据传感器的位置，从每个加速度周期的四分位数的平均值和 x-、y-和 z-方向的总加速度得到的变量。该组提取了一个组分，其表现出 95.4% 的方差，并被命名为特征 e。第六组包括

42 variables, which were obtained from the mean of the vari-ability per cycle of angular velocity in the x- and z-directions of all sensors except sensors 1 and 16. The component extracted from this group exhibited 93.6% variance and was named feature *F*. The seventh group included 12 variables, which were obtained from the mean of the standard deviation per cycle of angular velocity in the y-direction. The component extracted from this group used the variables obtained from sensors 3 to 14, exhibited 96.4% variance, and was named feature *G*. The eighth group included 23 variables, which were obtained from the variability of the location per cycle of angu-lar velocity in the y-direction. The variables were obtained from sensors 4 to 15. The component extracted from this group exhibited 91.3% variance and was named feature *H* . The ninth group included 20 variables, which were obtained from the variability of the location per cycle of angular velocity in the
这些变量是从除传感器 1 和 16 之外的所有传感器在 x 和 z 方向的每个角速度周期的变化能力的平均值得出的。从该组中提取的组分表现出 93.6% 的方差，并被命名为特征 f。第七组包括 12 个变量，这些变量是从 y 方向每个角速度周期的标准差的平均值得到的。从该组提取的组分使用从传感器 3 到 14 获得的变量，表现出 96.4% 的方差，并被命名为特征 g。第八组包括 23 个变量，这些变量是从 y 方向角速度每个周期位置的变化中获得的。变量从传感器 4 到 15 获得。从该组中提取的组分表现出 91.3% 的方差，并被命名为特征 h。第九组包括 20 个变量，这些变量是从角速度每个周期位置的变化中获得的

z-direction. The variables were obtained from sensors 3 to
Z 方向。变量从传感器 3 获得到

14. The component extracted from this group exhibited 88.2% variance and was named feature *I* . The tenth group included
从该组中提取的成分方差为 88.2%， 命名为特征 i

18 variables, which were obtained from the variability of the location per cycle of acceleration and the total acceleration in the x-, y-, and z-directions depending upon the location of the sensors. The variables for this component were extracted from sensors 1, 2, 3, 4, 7, 8, 11, 14, and 15. This component exhibited 86.7% variance and was named feature *J* . The eleventh group included 11 variables, which were obtained from the variability of the location per cycle of acceleration in the x-direction. The variables for this component were extracted from sensors 6, 7, 9, 10, and 12. The component extracted from this group exhibited 89.8% variance and was named feature *K* . The twelfth group included 24 variables, which were obtained from the location of the location per cycle of angular velocity in the y-direction. The variables for this component were extracted from sensors 3 to 14. The component extracted from this group exhibited 85.5% variance and was named feature *L*. The final group included four variables obtained from the location of the location per cycle of the angle. The variables for this component were extracted from sensors 8 and 11. The component extracted from this group exhibited 92.9% variance and was named feature *M*.

变量，这些变量是从每个加速周期的位置变化和总加速度在 x-，y-和 z 方向取决于传感器的位置。该组件的变量从传感器 1,2,3,4,7,8,11,14 和 15 中提取。该组件表现出 86.7% 的方差，被命名为特征 j。第十一组包括 11 个变量，这些变量是从 x 方向上每个加速周期位置的变化中获得的。该组件的变量从传感器 6,7,9,10 和 12 中提取。从该组中提取的组分表现出 89.8% 的方差，并被命名为特征 k。第十二组包括 24 个变量，这些变量是从每个周期的角速度在 y 方向的位置得到的。这个组件的变量从传感器 3 提取到 14。从该组中提取的组分表现出 85.5% 的方差，并被命名为特征 l。最后一组包括从每个角度周期的位置获得的四个变量。这个组件的变量是从传感器 8 和 11 中提取的。从该组提取的组分表现出 92.9% 的方差，并被命名为特征 m。

The variables extracted from the GT were classified into six groups. The first group included ten variables obtained from the mean of the interquartile per cycle of angular velocity in the y-direction. The variables for this component were extracted from sensors 2, 3, 4, 5, 8, and 11 to 15. The compo-nent extracted from this group exhibited 96.6% variance and was named feature *N*. The second group included 11 variables, which were obtained from the mean of the interquartile per cycle of angular velocity in the z-direction. The variables for this component were extracted from sensors 3, 4, and 6 to

从 GT 中提取的变量被分为六组。第一组包括从 y 方向每个角速度周期的四分位数的平均值获得的十个变量。该组件的变量从传感器 2,3,4,5,8 和 11 至 15 中提取。从该组中提取的组分表现出 96.6% 的方差，并被命名为特征 n。第二组包括 11 个变量，这些变量是由 z 方向每个角速度周期的四分位数的平均值得到的。该组件的变量从传感器 3,4 和 6 提取到

14. The component extracted from this group exhibited 94.4% variance and was named feature *O*. The third group included
从该组提取的组分表现出 94.4% 的方差，并被命名为特征 o。包括第三组

17 variables obtained from the mean of the interquartile per cycle of angular velocity in the x- and z-directions. The variables for this component were extracted from sensors 2, 3, and 6 to 13. The component extracted from this group exhibited 95.2% variance and was named feature *P*. The fourth group included 12 variables, which were obtained from the mean of the standard deviation per cycle of angular velocity in the y-direction. The variables for this component were extracted from sensors 3 to 14. The component extracted from this group exhibited 96.4% variance and was named feature *Q*. The fifth group included 11 variables, which were obtained from the mean of the interquartile per cycle of angular velocity in the y-direction. The variables for this component were extracted from sensors 6 to 15. The component extracted from this sensor exhibited 96.4% variance and was named feature *R*. The final group included 12 variables obtained from the mean of the interquartile per cycle of the angular velocity in the x-direction. The variables for this component were extracted from sensors 5 to 15. The component extracted from this feature exhibited 95.8% variance and was named feature *S*.

变量从每个周期的角速度在 x 和 z 方向的四分位数的平均值获得。该组件的变量从传感器 2,3 和 6 至 13 中提取。从该组中提取的组分表现出 95.2% 的方差，并被命名为特征 p。第四组包括 12 个变量，这些变量是从 y 方向每个角速度周期的标准差的平均值得到的。这个组件的变量从传感器 3 提取到 14。从该组中提取的组分表现出 96.4% 的方差，并被命名为特征 q。第五组包括 11 个变量，这些变量是根据 y 方向每个角速度周期的四分位数的平均值得出的。该组件的变量从传感器 6 至 15 中提取。从该传感器提取的组分表现出 96.4% 的方差，并被命名为特征 r。最后一组包括从 x 方向角速度每个周期的四分位数的平均值获得的 12 个变量。这个组件的变量从传感器 5 提取到 15。从该特征提取的组件表现出 95.8% 的方差，并被命名为特征 s。

4) Feature Selection, LR, and Performance Evaluation: The ability of these constructed features to predict the participants'
特征选择、 LR 和性能评估: 这些构建的特征预测参与者的能力

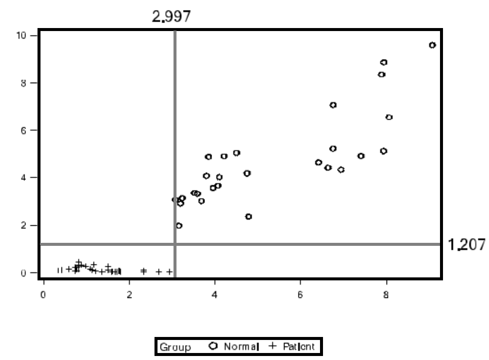


Fig. 9. Scatter plot of standard deviation and interquartile of angular velocity in the y-axis for the TT.
图 9。 TT 在 y 轴上的标准差和角速度四分位数的散点图。

status was assessed using the LR based on data from all three tasks. Backward selection with removal criterion 0.05 was set to select the most influential features. Standardized estimates were used to evaluate the importance of the predictors. The receiving operator characteristic (ROC) curve and the area under the ROC curve (AUC) were computed to evaluate the predictive power of the models. Finally, the Kruskal–Wallis test was employed to investigate the ability of the con-structed features in classifying the severity of hand movement dysfunction.
根据来自所有三个任务的数据，使用 LR 评估状态。设置具有去除标准 0.05 的向后选择以选择最有影响的特征。使用标准化估计来评估预测因子的重要性。计算接受操作者特征曲线(ROC)和 ROC 曲线下面积(AUC)，评价模型的预测能力。最后，使用 Kruskal-Wallis 检验来研究构建特征在分类手运动功能障碍严重程度方面的能力。

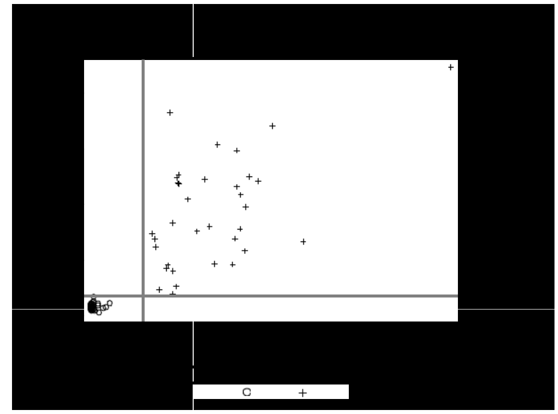
III. Results
结果

A. Classification Between HS and SP
HS 和 SP 之间的分类

In this experiment, Y denoted the status of the response variable, in which 1 denoted an SP and 0 denoted an HS. In addition, x denoted the vector of the predictor variables in general. The ability to classify the SPs and HSs was evaluated for each task.

在本实验中，y 表示响应变量的状态，其中 1 表示 SP，0 表示 HS。另外，x 一般表示预测变量的向量。对每个任务评估分类 SPs 和 HSs 的能力。

1) Results of the TT: Only two variables, standard deviation and interquartile range, that measured the variability of angu-lar velocity in the y-direction from sensor 1 were selected. LR yielded a perfect fit. Fig. 9 presents a scatter plot of variables' standard deviations and interquartile ranges. Based on this scatter plot, the HSs corresponded to high variability, whereas the SPs corresponded to low variability. The scatter plot shows that the threshold between SPs and HSs was 2.997 for standard deviation and 1.207 for interquartile range. This difference clearly distinguishes the two groups.



1)测试结果: 只选取了标准差和四分差这两个测量传感器 1 在 y 方向上角速度变化的变量。LR 产生了完美的匹配。图 9 显示了变量的标准偏差和四分位间距的散点图。基于这个散点图，HSs 对应于高变异性，而 SPs 对应于低变异性。散点图显示标准差和四分差的阈值分别为 2.997 和 1.207。这种差异清楚地区分了两组。

2) Results of the GT: Six features were identified. LR yielded a perfect fit for P, R, and S. Fig. 10 presents the scatter plots of P, R, and S. Based on the three scatter plots in Fig. 10, SPs have high values of P, R, and S, whereas HSs have small values of P, R, and S.

2) GT 的结果: 识别出 6 个特征。LR 得到了 p，r 和 s 的完美拟合。图 10 给出了 p，r 和 s 的散点图。根据图 10 中的三个散点图，SPs 具有高的 p，r 和 s 值，而 HSs 具有小的 p，r 和 s 值。

3) Results of the CTT: Based on the removal criterion 0.05 for the backward selection and using only the recordings from the CTT, features B, C, D, and K were selected from the CTT. LR for this case was calculated according to (1). The selected features for the CTT are listed in Table II.

3) CTT 结果: 根据后向选择的去除标准 0.05，仅使用 CTT 的记录，从 CTT 中选择特征 b、 c、 d 和 k。根据(1)计算这种情况的 LR。表 II 列出了 CTT 选定的特性。

$$\log \frac{P[Y=1|x]}{P[Y=0|x]} = -1.58 - 3.61B + 2.25C + 3.00D - 1.96K. \quad (1)$$

log 日志 P [y = 1 | x] / P [y = 0 | x] =-1.58-3.61 b + 2.25 c + 3.00 d-1.96 k。(1)

Fig. 10. Scatter plot of features P, R and S for the GT: (a) features P and S, (b) features R and S, and (c) features P and R.
图 10。GT 特征 p、 r 和 s 的散点图: (a)特征 p 和 s，(b)特征 r 和 s，(c)特征 p 和 r。

TABLE II
表二

Selected Features in the CTT Model
CTT 模型中的特征选择

			p	Std Est	c
Intercept	-1.58	0.64	0.014		0.98
B	-3.61	0.94	<.001	-7.76	
C	2.25	0.79	0.004	3.37	
D	3.00	0.78	<.001	5.43	
K	-1.96	0.69	0.005	-2.62	

In the experiment, *B* and *K* were negatively associated with the event, whereas *C* and *D* were positively associated with the event. *B* and *D* were the most influential features. The ROC curve and AUC of the CTT model are presented in Fig. 11, revealing that the predictive power of this model was 0.98.

在实验中，b 和 k 与事件呈负相关，而 c 和 d 与事件呈正相关。B 和 d 是最有影响力的特征。图 11 给出了 CTT 模型的 ROC 曲线和 AUC，表明该模型的预测能力为 0.98。

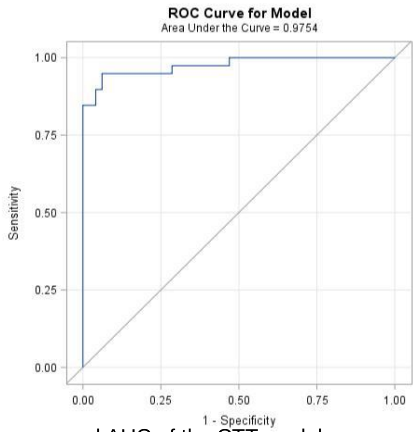


Fig. 11. ROC curve and AUC of the CTT model
图 11. CTT 模型的 ROC 曲线和 AUC

B. Classification Based on the Severity of the Subjects
B. 根据受试者的严重程度进行分类

The severity of the disease was measured in terms of BSs. Moreover, SPs were further classified into BS4 and BS5. The variable Z denoted the status of the severity, in which 0 denoted HS, 1 denoted BS5, and 2 denoted BS4. Among 218 recordings, 25 recordings (11.5%) and 75 (34.4%) were collected from BS4 and BS5 participants, respectively. For each task, only nine, eight, and eight recordings were collected from BS4.

病情的严重程度用 BSs 来衡量。此外，SPs 进一步分为 bs4 和 BS5。变量 z 表示严重程度的状态，其中 0 表示 HS，1 表示 BS5,2 表示 BS4。在 218 个记录中，分别从 bs4 和 bs5 参与者收集了 25 个记录(11.5%)和 75 个(34.4%)。对于每个任务，只有 9,8 和 8 个记录从 bs4 收集。

The Kruskal–Wallis test was used to compare the three groups. Furthermore, it was used again to compare BS4 and BS5. The results are presented in Table III. These show signifi-cant differences in the results of the 13 features extracted from the CTT and 6 features extracted from the GT between the SPs and HSs. Further comparison revealed that the difference in these features between BS4 and BS5 was nonsignificant.

使用 Kruskal-Wallis 测试来比较三组。此外，它又被用来比较 bs4 和 BS5。结果如表 III 所示。这些显示了从 CTT 提取的 13 个特征和从 SPs 和 HSs 之间的 GT 提取的 6 个特征的结果的显着差异。进一步的比较显示 bs4 和 bs5 之间这些特征的差异不显着。

Fig. 12 presents box plots of the selected variables for the three groups while conducting the TT. For the TT, the variable measuring the standard deviation of angular velocity in the y-direction from sensor 1 exhibited considerable differences among the three groups. However, the variable that measured the interquartile range of angular velocity in the y-direction from sensor 1 exhibited a considerable difference between the SPs and HSs but only a small difference between BS4 and BS5.

图 12 显示了进行 TT 时三组所选变量的框图。对于 TT 来说，测量来自传感器 1 的 y 方向角速度标准差的变量在三组之间表现出相当大的差异。然而，从传感器 1 测量 y 方向角速度四分差范围的变量显示了 SPs 和 HSs 之间的相当大的差异，但是 bs4 和 bs5 之间只有很小的差异。

Table IV compares the previous method [14] with that of the present study. For feature extraction and selection, the previous method mainly obtains features by observing the characteristics of the subjects’ movements while they perform the TT, GT, and CTT. However, the proposed method in the present study adopts statistical methods to analyze the raw data and extract all possible features. Next, PCA is adopted to reduce the dimensions of the data set, and the most influential features are selected using backward selection. Therefore, the previous method could not create a stable model for predicting severity, whereas the proposed method can create a stable model with influential features for performing predictions. Regarding the information provided by the two methods, the previous method only provides three features for the overall evaluation, whereas the proposed method provides influential

表 IV 比较了以前的方法[14]与本研究的方法。在特征提取和选择方面，以往的方法主要通过观察被试在进行 TT、 GT 和 CTT 时的运动特征来获取特征。然而，在本研究中提出的方法采用统计方法来分析原始数据和提取所有可能的特征。Next 采用 PCA 来减少数据集的维数，并且使用向后选择来选择最有影响的特征。因此，以前的方法不能建立一个稳定的模型来预测严重程度，而提出的方法可以建立一个稳定的模型与有影响的特征进行预测。关于这两种方法提供的信息，以前的方法只为整体评估提供了三个特征，而提出的方法提供了有影响力的

features for each task. Moreover, the most important sensor positions and tasks are provided to enhance the quality and efficiency of future manual dexterity assessment. Therefore, more comprehensive information can be obtained by adopting the proposed method than by adopting the previous method.
每项任务的特性。此外，提供了最重要的传感器位置和任务，以提高未来手工灵活性评估的质量和效率。因此，通过采用所提出的方法可以获得比采用以前的方法更全面的信息。

IV. Discussion
四、讨论

In this study, three tasks were conducted to evaluate the participants' hand function. PCA was conducted to create specific features for the GT and CTT. The performance and most influential predictor of each task are presented in Figs. 9, 10, and 11 as well as Table II to differentiate between the HSs and SPs. Fig. 9 shows that the standard deviation and interquartile range of angular velocity in the y-axis from sensor 1 were the most influential predictors in the TT. This result indicated that a subject was an SP if the two predictors were low. Moreover, the results indicated that the position of sensor 1 was important for the TT. This is primarily because the two predictors represent the mobility of a subject's thumb, and HSs have higher mobility in their thumbs than that of SPs. Fig. 10 shows that the features *P*, *R*, and *S* were the most important predictors for the GT. Furthermore, this result implied that a participant was an SP if the values of *P*, *R*, and *S* were high. The features *P*, *R*, and *S* were mainly composed of the interquartile range of acceleration in the z-axis and the interquartile range of angular velocity in the x- and y-axis after normalization. Low values of the three features indicated highly stable hand function. HSs demonstrated high stability when the GT was performed and tended to be in a similar range of values because of the normalization; however, SPs exhibited low stability when the GT was performed and were not in a specific range. Table II shows that features *B* and *D* were the most influential predictors for the CTT, which implied that a participant was an HS if the value of *B* was high and that of *D* was low. Feature *B* was mainly composed of the average standard deviation of acceleration in the z-axis from the sensors on the index, middle, ring, and little fingers. Feature *B* represented the hand mobility of the participant when the CTT was performed. Thus, the HSs had higher hand mobility than the SPs did. Feature *D* mainly consisted of the average standard deviation of acceleration in the y-axis from the whole sensors on the hand except the sensor on the thumb. Moreover, *D* represented the horizontal tremor of the hand when performing the CTT. This indicates that SPs may have had considerable tremors on their hands when performing the CTT. Overall, the results revealed that the three tasks could accurately differentiate SPs and HSs. Furthermore, classification of SPs and HSs using the TT and GT could attain a predictive power of 1.0, whereas CTT could attain a predictive power of 0.98.

在这项研究中，我们进行了三项任务来评估参与者的手功能。进行 PCA 以为 GT 和 CTT 创建具体特征。每个任务的表现和最有影响力的预测因子在图 9、10 和 11 以及表 II 中给出，以区分 HSs 和 SPs。图 9 显示，来自传感器 1 的 y 轴上角速度的标准差和四分差范围是 TT 中最有影响的预测因子。这个结果表明，如果两个预测因子较低，则受试者是 SP。此外，结果表明传感器 1 的位置对于 TT 是重要的。这主要是因为这两个预测因子代表了受试者拇指的移动性，并且 HSs 在其拇指中的移动性高于 SPs。图 10 显示特征 p，r 和 s 是 GT 最重要的预测因子。此外，这个结果意味着如果 p，r 和 s 的值很高，则参与者是 SP。特征 p、 r 和 s 主要由归一化后 z 轴加速度的四分差范围和 x 轴和 y 轴角速度的四分差范围组成。三个特征的低值表明手功能高度稳定。结果表明，高温超导热稳定性较高，且由于标准化作用，其稳定性趋于相近；而高温超导热稳定性较低，且不在特定范围内。表 II 显示，特征 b 和 d 是 CTT 最有影响的预测因子，这意味着如果 b 值高而 d 值低，参与者就是 HS。特征 b 主要由食指、中指、无名指和小指的加速度在 z 轴上的平均标准差组成。特征 b 表示 CTT 进行时参与者的手部移动性。因此，HSs 比 SPs 具有更高的手动性。特征 d 主要包括除拇指上的传感器外，手上所有传感器在 y 轴上加速度的平均标准差。此外，d 代表进行 CTT 时手的水平震动。这表明 SPs 在进行 CTT 时手部可能有相当大的震颤。总体而言，结果显示这三项任务可以准确区分 SPs 和 HSs。此外，用 TT 和 GT 对 SPs 和 HSs 进行分类，其预测能力为 1.0，而 CTT 的预测能力为 0.98。

A crucial aspect of the hand function assessment described herein is measuring disease severity. The disease severity calculated from the experiment is presented in Table III. This shows that the three proposed tasks could be used to accurately classify HS, BS4, and BS5; however, for classification of BS4 and BS5, only the standard deviation of angular velocity when conducting the TT could differentiate BS4 and BS5.

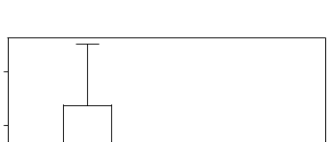
本文描述的手功能评估的一个关键方面是测量疾病的严重程度。表 III 列出了从实验计算的疾病严重程度。结果表明，所提出的三个任务可以用来准确地分类 HS、 bs4 和 BS5，而对于 bs4 和 bs5 的分类，只有进行测试时角速度的标准差才能区分 bs4 和 BS5。

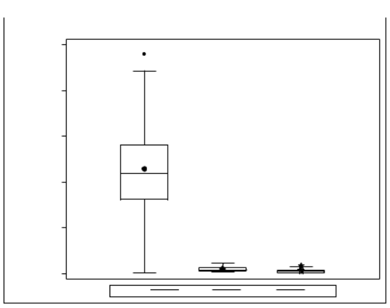
TABLE III
表三
SELECTED VARIABLES IN EACH TASK FOR MEASURING DISEASE SEVERITY
测量疾病严重程度的每个任务中的选定变量

		HS		BS5		BS4			
			Error	Mean	STD Error	Mean	STD Error	p*	p&
TT	QRANGE of angular velocity							<.001	0.082
	STD of angular velocity							<.001	<.001
GT	N	-2.10	0.29	1.51	2.43	1.60	1.13	<.001	0.338
	O	-1.98	0.42	2.11	2.63	2.38	1.46	<.001	0.602
	P	-2.97	0.87	2.21	2.99	3.11	1.61	<.001	0.098
	Q	0.22	0.92	0.81	2.66	1.27	1.74	0.401	0.514
	R	-2.12	0.33	1.53	2.42	1.76	1.56	<.001	0.459
	S	-1.98	0.46	2.13	2.38	2.87	2.54	<.001	0.433
CTT									

p*means the p
p& means the p

p indicates the p
c





(b)

Fig. 12. Box plots of the selected features for the three groups while conducting TT: (a) standard deviation of angular velocity in the y-axis from sensor 1 and (b) interquartile range of the angular velocity in the y-axis from sensor 1.

图 12。进行 TT 时三组选定特征的盒图: (a)传感器 1 的 y 轴角速度的标准差和(b)传感器 1 的 y 轴角速度的四分差范围。

TABLE IV
表四
COMPARISON BETWEEN THE PREVIOUS METHOD AND PROPOSED METHOD
前一种方法与建议方法

	Observation and Selection	and PCA
Stable Model	No	LR
Features	5 features	2 features for TT, 4 features for GT, 13 features for CTT
Sensor Positions	No	Yes
Tasks	No	Yes

Box plots presented in Fig. 12 indicate the features from the TT to differentiate HS, BS4, and BS5. The TT was the only task that could accurately differentiate SPs in BS4 and BS5.
图 12 中所示的方块图表示 区分 HS、bs4 和 BS5。TT 是唯一能够准确区分 bs4 和 bs5 中 SPs 的任务。

However, the TT only provided the features of a thumb. By contrast, the GT and CTT could extract more features of hand function, but the limited samples in BS4 reduced the accuracy of prediction from the GT and CTT when differentiating BS4 and BS5. If the samples of BS4 increased, the perfor-mance of the GT and CTT would increase when classifying BS4 and BS5. Therefore, if physicians require additional hand function features, the GT and CTT would be preferable for classifying the severity of hand dysfunction. In the future, the GT and CTT could be used to provide detailed information regarding manual dexterity if more clinical data are collected.

然而，TT 只提供了拇指的特征。相比之下，GT 和 CTT 可以提取更多的手功能特征，但 bs4 的有限样本降低了区分 bs4 和 bs5 时 GT 和 CTT 的预测精度。如果 bs4 的样品增加，则在分类 bs4 和 bs5 时，GT 和 CTT 的性能将增加。因此，如果医生需要额外的手功能特征，GT 和 CTT 对于分类手功能障碍的严重程度是可取的。将来，如果收集更多的临床数据，GT 和 CTT 可以用来提供有关手动灵活性的详细信息。

V. Conclusion
结语

In this study, LR was used to analyze raw data from a data glove equipped with six-axis IMUs and to extract the representative hand function parameters. Three tasks—the TT, GT, and CTT—were conducted to evaluate the hand function of patients with stroke. The results revealed that the proposed tasks could be used to accurately differentiate HS and SP. The

在这项研究中，LR 被用来分析一个装有六轴 IMUs 的数据手套的原始数据，并提取代表性的手功能参数。进行三项任务(TT，GT 和 ctt)来评估中风患者的手功能。结果显示，提出的任务可以用来准确区分 HS 和 sp。他说

TT and GT could precisely 100% separate HS and SP, and the CTT reached a predictive power of 0.98. The TT exhibited the most accurate performance in identifying hand dysfunction severity among the participants. Therefore, the TT is the most effective method of differentiating HSs and SPs as well as identifying dysfunction severity.

GT 可以 100% 精确地分离 HS 和 SP，CTT 达到 0.98 的预测能力。TT 在识别参与者手功能障碍严重程度方面表现出最准确的表现。因此，TT 是区分 HSs 和 SPs 以及鉴别功能障碍严重程度的最有效方法。

The lower performance of the GT and CTT in determining dysfunction severity was because of the limited number of BS4 participants. However, the GT and CTT can provide additional manual dexterity information compared with using the TT. Therefore, more participants should be recruited in BS4 in future studies to improve the performance of prediction using the GT and CTT.

GT 和 CTT 在确定功能障碍严重程度方面的表现较差是因为 bs4 参与者的数量有限。然而，与使用 TT 相比，GT 和 CTT 可以提供额外的手动灵活性信息。因此，在未来的研究中，应该在 bs4 中招募更多的参与者，以提高使用 GT 和 CTT 的预测性能。

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