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A Study of Hand Function in Stroke Patients Using Kinematic Metrics

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***Abstract*—Currently, many methods for assessing hand function in stroke patients are administered by humans, which can lack objectivity and make it difficult to achieve precise evaluations. In order to tackle this issue, we proposed a new assessment method that utilized hand movement data collected from the Leap motion device. By applying the independent sample T-test or Mann-Whitney U-test, we identified sensitive kinematic metrics from the 38 extracted metrics. We then used the principal component analysis (PCA) method to further analyze and rank the selected sensitive metrics. This processing enabled us to determine the most sensitive kinematic metrics that can distinguish differences in hand function between normal individuals and stroke patients. To validate the proposed method, we conducted an experiment with 15 volunteers. The results showed that MiddleMCP-Max was the most sensitive metric for distinguishing patients from normal individuals. The experimental results also demonstrated that the proposed method was effective, scientifically objective, and may be useful in assisting with the hand function evaluation of stroke-induced hemiplegia.**

Keywords- Stroke patients; Kinematic metrics; Hand function; Principal component analysis.

I. Introduction

Clinical evaluation is crucial for stroke patients as it allows for assessing rehabilitation outcomes, evaluating treatment effectiveness, and providing guidance and recommendations for future therapy. In the clinical setting, hand function is often evaluated through the use of subjective scales such as the Brunnstrom assessment [1] and the Fugl-Meyer Assessment scale [2]. While the validity of these scales has been established through various studies, their primary drawback is that the assessment results are based on the therapist's subjective judgment [3]. To solve this limitation, computer-aided technologies such as biomechanical testing, surface electromyography (sEMG), and upper-limb robotics can provide more objective assessment outcomes for rehabilitation [4]. These technologies can enhance hand motor dysfunction recovery in stroke patients. Still, their single rehabilitation mode lacks interaction and adaptability to varying rehabilitation needs and stages, resulting in the poor initiative and adaptability issues.

Ultraleap's Leap Motion Controller (LMC) is a gesture detection device that was released in 2013. It uses advanced technology to detect hand and finger movements without complex physical markers, making it a helpful tool for the hand rehabilitation assessment. Compared to Microsoft's Kinect series, the LMC is smaller, lighter, and more cost-effective, making it more suitable for use in clinical settings. Several studies have shown that the LMC is reliable and accurate in capturing hand movement data and can objectively evaluate hand function [5].

Kinematic metrics analysis is a leading research topic for rehabilitation assessment, but identifying the most sensitive metrics for hand movements remains a challenge. Meanwhile, most existing kinematic metrics have not been adequately studied for hand movements. Their measurement requires a specialized motion capture system, which may not be feasible for home or community use. Therefore, the principal objective of this study is to identify sensitive kinematic metrics using the LMC device for differentiating stroke patients from healthy individuals. To validate this method, 15 volunteers were recruited for an experiment.

II. Method

Fig. 1 illustrates the block diagram of the technical approach of this study. It involves the use of a dynamic capture system (i.e., LMC) to acquire hand movement data, followed by preprocessing of the raw data, which includes missing data checking, filtering, segmentation processing, and classification. Using a hand mechanics model, the preprocessed data is then used to calculate 38 metrics from angular and other kinematic metrics. To screen out the sensitive metrics that can reflect significant differences between stroke patients and healthy subjects, the data is analyzed for normal distribution, followed by the independent sample T-test or Mann-Whitney U-test. Finally, the PCA (principal component analysis) method is used to identify the most sensitive metrics.

A. Subjects

The study recruited 10 stroke patients and 5 healthy subjects, aged 18 to 80 years old, without any history of complex diseases. The patients were recommended by occupational therapists and

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the control group was recruited by the Fujian University of Traditional Chinese Medicine. All subjects provided informed consent according to the Declaration of Helsinki, and the research protocol was approved by the ethics review committee of Fujian Rehabilitation Hospital.

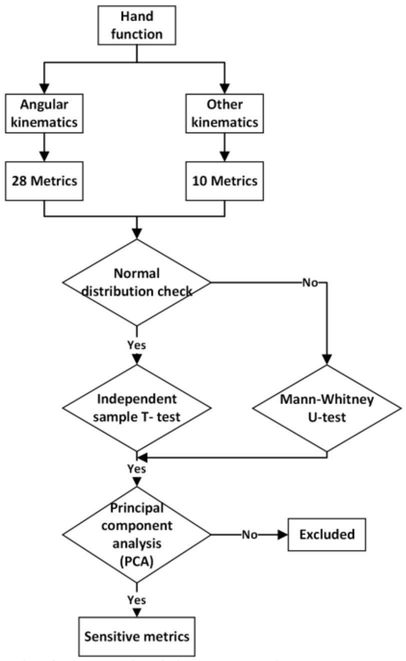

Fig.1. The framework of the proposed assessment method.

B. *Protocol*

The experiment involved 6 functional tasks for all 10 fingers:

Task-I: Starting position with forearm rotated back and fingers extended, then all fingers flex and extend;

Task-II to **VI**: Starting position with forearm rotated back and individually flex and extend each finger sequentially.

During the experiment, participants performed finger flexion-extension movement tasks with their testing hand on a table. In contrast, the non-testing hand rested on their knee (Fig. 2). Tasks were repeated five times with a 3s pause between each repetition, with stroke patients using their affected hand and healthy participants using their dominant hand. The LMC (Leap Motion Controller) was used in the study to acquire the hand data of participants. They were seated in a chair (45cm off the ground) in front of a table (75cm off the ground) with the LMC set up 50cm away from them. The data was saved in an xlsx file at a default frequency of 30Hz.


Fig.2. Experimental procedure.

C. *Kinematic metrics analysis*

Hand kinematic measurements were classified into two groups: angular kinematic metrics and other kinematic metrics. From these two categories, 38 metrics (28 angular kinematics and 10 other kinematic metrics) were chosen [6], and the specific characteristics of the metrics were provided in the TABLE. I.

I) Angular kinematic metrics: the metrics primarily refer to the angles of the finger joints, including the metacarpophalangeal (MCP), distal interphalangeal (DIP), and proximal interphalangeal (PIP) joints (Fig. 3). The joint angles of the fingers are shown in Fig. 4. These metrics are useful for comparative analysis since stroke patients with hand hemiplegia often experience reduced angles of finger extension and flexion [7]. The equations used to calculate the finger joint angles are as follows [6]:

$$\theta_1 = cos^{-1}\left(\frac{\overrightarrow{WM} \cdot \overrightarrow{MP}}{\|\overrightarrow{MP}\| \cdot \|\overrightarrow{WM}\|}\right) \tag{1}$$

$$\theta_2 = cos^{-1}\left(\frac{\overrightarrow{MP} \cdot \overrightarrow{PD}}{\|\overrightarrow{MP}\| \cdot \|\overrightarrow{PD}\|}\right) \tag{2}$$

$$\theta_3 = cos^{-1}\left(\frac{\overrightarrow{PD} \cdot \overrightarrow{DT}}{\|\overrightarrow{PD}\| \cdot \|\overrightarrow{DT}\|}\right) \tag{3}$$

In the equations, W, M, P, D, and T represent the wrist, metacarpophalangeal (MCP), proximal interphalangeal (PIP), distal interphalangeal (DIP), and the tip of the finger, respectively. WM, MP, PD, and DT represent the bones at the base of the palmar phalanx, proximal phalanx, middle phalanx, and distal phalanx, respectively. The angles between the bones are represented by θ_1, θ_2, θ_3, which stands for the angle between the bones at the base of the palm and proximal bone, proximal bone and middle bone, and middle bone and distal bone, respectively [6].

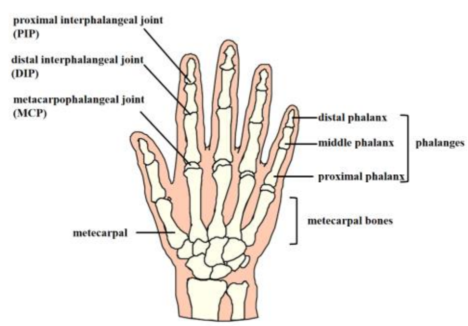

Fig.3. Hand structure diagram.

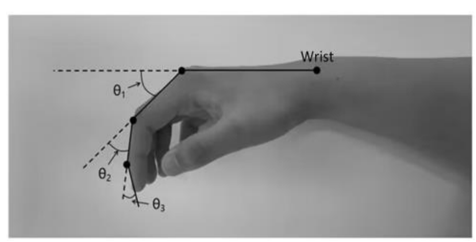

Fig.4. Finger joint angles.

II) Other kinematic metrics: the individuation index and the stationarity index, as proposed by Schieber et al. [8], quantify movement independence and stability, respectively.

TABLE.I KINEMATIC METRICS

Angular kinematic metrics					Other kinematic metrics	
ThumbDIP-Max	IndexMCP-Max	IndexDIP-Max	MiddleMCP-Max	MiddleDIP-Max	ThumbMCP-II	ThumbMCP-SI
RingMCP-Max	RingDIP-Max	LittleMCP-Max	LittleDIP-Max	ThumbPIP-Max	IndexMCP-II	IndexMCP-SI
IndexPIP-Max	MiddlePIP-Max	RingPIP-Max	LittlePIP-Max	ThumbPIP-Min	MiddleMCP-II	MiddleMCP-SI
IndexPIP-Min	MiddlePIP-Min	RingPIIP-Min	LittlePlP-Min	ThumbDIP-Min	RingMCP-II	RingMCP-SI
MiddleDIP-Min	MiddleMCP-Min	IndexDIP-Min	IndexMCP-Min	RingDlP-Min	LittleMCP-II	LittleMCP-SI
RingMCP-Min	LittleDIP-Min	LittleMCP-Min				

a) Individuation index (II): to evaluate the independence of a digit's movement, representing the degree of independence of the instructed digit's movement. An ideal digit would only move when instructed and not move during the instructed movement of other digits. The index is calculated as follows:

$$\mathrm{II}_j = 1 - \frac{[(\sum_{i=1}^{n}|S_{ij}|) - 1]}{(n-1)} \tag{4}$$

In the formula, II_j represents the individualization index of the jth finger when performing the specified movement, S_{ij} refers to the relative angular displacement of the ith finger of the jth finger while performing the indicative movement, and n is the number of fingers (n=5). The ideal individualized movement has an index close to 1, indicating that the indicated finger does not move when the non-indicated finger moves. If the non-indicated finger moves with the pointed finger, the index is close to 0 [9].

b) Stationarity index (SI): to quantify the degree of movement of a digit during non-instruction, indicating the stability of the finger. The index is calculated as follows:

$$SI_i = 1 - \frac{[(\sum_{j=1}^{m}|S_{ij}|)]}{(m-1)} \tag{5}$$

In the formula, SI_i represents the stationarity index of the ith finger during the mth indicative action (m=5). If a finger remains stationary when acting as a non-guiding finger, the value of SI will be close to 1; otherwise, if it acts as a non-guiding finger, the greater the movement, the closer the value of SI is to 0 [9].

D. Data processing and analysis

I) Pre-processing: customized processing software is developed to search for errors in the raw data (such as missing data) measured by the LMC. Corrections are made based on the average value of upper and lower values. It's worth noting that in terms of data representation, the movement data of healthy people generally presents a regular hump shape (Fig. 5(a)), whereas when the device itself has faults or the patient's hand movement has limitations, the data imaging is not ideal, and there is no obvious hump appearing (Fig. 5(b)).

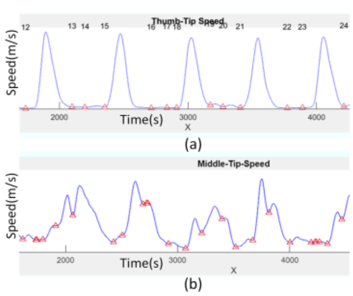

Fig.5. Performance representation chart:
(a) normal performance, and (b) abnormal performance.

After completing the error data check and correction, data is segmented based on the desired number of repetitions, with the number of segments equal to the number of repetitions. Then, 90% of the maximum velocity is extracted from each segment to make the data more concentrated and powerful in representation [10].

II) Formal processing: standard processing is the further processing of the data that has undergone preprocessing. This step involves the final data calculation of the kinematic metrics for each finger by MCP (metacarpophalangeal) data. It is worth noting that there is no need to consider left and right hand differences as data obtained from the LMC is from one hand.

III) The independent sample T-test: the independent sample T-test, also known as the two-sample T-test, is used to determine if there is a significant difference between the means of two independent groups. It is used when the sample size is small (n<30), and the population standard deviation is unknown. The T-test uses the t-distribution theory to calculate the probability of differences between the means, which is compared to a chosen significance level (e.g., 0.05) to determine statistical significance. If the *p*-value is less than the significance level, there is a significant difference between the means of the two groups [11].

IV) The Mann-Whitney U-test: this test is a nonparametric statistical test used to determine significant differences between two independent samples when assumptions of normality and equal variances are not met [12]. It compares the ranks of the values in the samples, calculates a U-statistic, and determines a *p*-value. If the *p*-value is less than a chosen significance level (e.g., 0.05), it is concluded that there is a significant difference between the samples.

V) PCA (Principal Component Analysis) method: PCA is a statistical method commonly used to reduce the dimensionality of data. It employs linear algebra to transform correlated variables into uncorrelated principal components, ranked by their variance (the first principal component has the highest variance, and so on.). This technique is used in a wide range of fields, including image processing, face recognition, and bioinformatics [13], due to its ability to extract the most significant features while retaining essential information.

III. Results

This study mainly focused on identifying sensitive metrics for six functional tasks using statistical tests like the independent sample T-test and Mann-Whitney U-test. By applying these tests along with the PCA method, the study successfully detected significant differences between the results of stroke patients and healthy individuals. Due to the comprehensive nature of Task-I and the high level of repetitiveness in the other tasks, the analysis primarily focuses on a detailed examination of the results from Task-I to make the presentation more concise.

After analyzing the data from Task-I, it was discovered that all fingers except for the thumb and middle had only one sensitive metric (MiddleMCP-Max), which did not meet the conditions for PCA. As a result, the significant metric was utilized directly for the classification analysis of stroke patients and healthy individuals. On the other hand, the thumb and index had two sensitive metrics each (MiddleMCP-Max and LittlePIP-Min for the thumb, and RingPIP-Max and MiddleMCP-Max for the middle), allowing for the application of the PCA method.

The analysis focused on the thumb and index, where both had two sensitive metrics. PCA results showed that PC1 accounted for a more significant percentage than PC2 for the thumb (Fig. 6(a)). Thus, PC1 was emphasized when comparing data, and healthy individuals had mostly negative PC1 values, while patients had positive values (Fig. 6(b)). This result demonstrates that PCA can effectively distinguish between patients and healthy individuals. LittlePIP-Min contributed significantly more to PC1 than MiddleMCP-Max for the thumb (TABLE. II), indicating that LittlePIP-Min was the most sensitive kinematic metric. Similarly, RingPIPMax was the most sensitive kinematic metric for the index.

TABLE.II THE PROPORTION OF SIGNIFICANT METRICS IN THE PCA

Metric(ID)	PC1	PC2
MiddleMCPMax	0.074	0.997
LittlePIPMin	**0.997**	0.074

Significant metrics were used to analyze fingers that cannot use PCA (only the index is discussed in detail due to space limitations). As shown in Fig. 6(c), the values of healthy individuals after averaging were concentrated around 70, while the data values of stroke patients were significantly higher than those of healthy individuals. Thus, it was demonstrated that significant metrics could differentiate between patients and healthy individuals, with MiddleMCPMax being the most sensitive kinematic metric.

The analysis process for Task-II through VI was similar to that of Task-I, so a detailed elaboration of the analysis process will not be provided. TABLE. III illustrated the percentage differences of the principal components for each task, and TABLE. IV presented the statistical results for the sensitive metrics.

TABLE.III PRINCIPAL COMPONENT PERCENT DIFFERENCE

Task	PC1%	PC2%	PC3%	PC4%	PC5%
Task-I (Thumb)	57.372	42.628	N/A	N/A	N/A
Task-I (Index)	N/A	N/A	N/A	N/A	N/A
Task-I (Middle)	75.675	24.325	N/A	N/A	N/A
Task-I (Ring)	N/A	N/A	N/A	N/A	N/A
Task-I (Pinky)	N/A	N/A	N/A	N/A	N/A
Task-II	81.856	8.757	6.890	1.947	0.549
Task-III	72.360	19.798	3.923	2.993	0.927
Task-IV	76.341	11.939	6.194	4.150	1.131
Task-V	92.645	7.355	N/A	N/A	N/A
Task-VI	78.860	21.140	N/A	N/A	N/A

The study found five sensitive metrics for Task-II, namely MiddleMCP-Max, MiddleDIP-Min, MiddlePIP-Min, MiddleMCP-II, and MiddleMCP-SI, which were validated through data analysis. After applying the PCA method and significance metric analysis, it was found that PC1 had the most significant proportion in the principal component analysis (81.86%), and MiddleMCP-SI had the highest ratio in PC1 (0.882). There was a significant numerical difference between patients and healthy individuals in the principal component analysis, indicating that MiddleMCP-SI was the most sensitive kinematic metric for distinguishing healthy individuals from patients with hand hemiparesis in Task-II.

Similarly, after data validation for Task-III, it was discovered that there were five sensitive metrics: IndexDIP-Max, MiddlePIP-Max, RingPIP-Max, MiddleDIP-Min, and MiddlePIP-Min. After PCA processing, it was found that among the 5 sensitive metrics, RingPIP-Max had the largest contribution to PC1 (accounting for 0.877), and the PC1 distribution of healthy individuals and patients had significant differences. Therefore, in this task, RingPIP-Max can be concluded as the most sensitive kinematic metric.

According to the data obtained, Task-IV had 6 sensitive metrics (MiddleDIP-Max, RingPIP-Max, MiddleDIP-Min, RingDIP-Min, RingPIP-Min, LittlePIP-Min). In contrast, Task- VI only had 2 metrics (IndexDIP-Min and MiddlePIP-Min). After performing the PCA method and significance metric analysis, MiddleDIP-Min was identified as the most sensitive metric, with proportions of 0.872 and 0.953 in PC1 for the two tasks.

Task-V was found to have 2 sensitive metrics: LittleMCP-Max and LittleMCP-II. After using the PCA method and performing significance metric analysis, it was determined that LittleMCP-II was the most sensitive kinematic metric for distinguishing between healthy individuals and hand hemiplegia patients. This was because it accounts for 0.872 of PC1, which has the highest proportion (92.65% among the principal components). Moreover, there is a notable numerical difference in PC1 between patients and healthy individuals. Therefore, it can be concluded that LittleMCP-II was the most sensitive kinematic metric for distinguishing healthy people and hand hemiplegia patients in Task-V.

IV. Discussion

This study investigated hand function in stroke patients using sensitive kinematic metrics. A total of 38 kinematic metrics were chosen through angular kinematics and other techniques. The independent sample T-test or Mann-Whitney U-test was used to identify the required sensitive metrics. The PCA method was applied to analyze the selected sensitive metrics further. The frequency at which various metrics were identified as sensitive varied among the different tasks. Therefore, the most sensitive kinematic assessment metric can be determined based on the frequency of appearance in the experimental assessment. According to Fig. 7, MiddleMCP-Max appeared 6 times, making it the most prominent metric, while MiddleMCP-Max, MiddleDIP-Min, and MiddlePIP-Min appeared 3 times and can be used as alternate sensitive metrics.

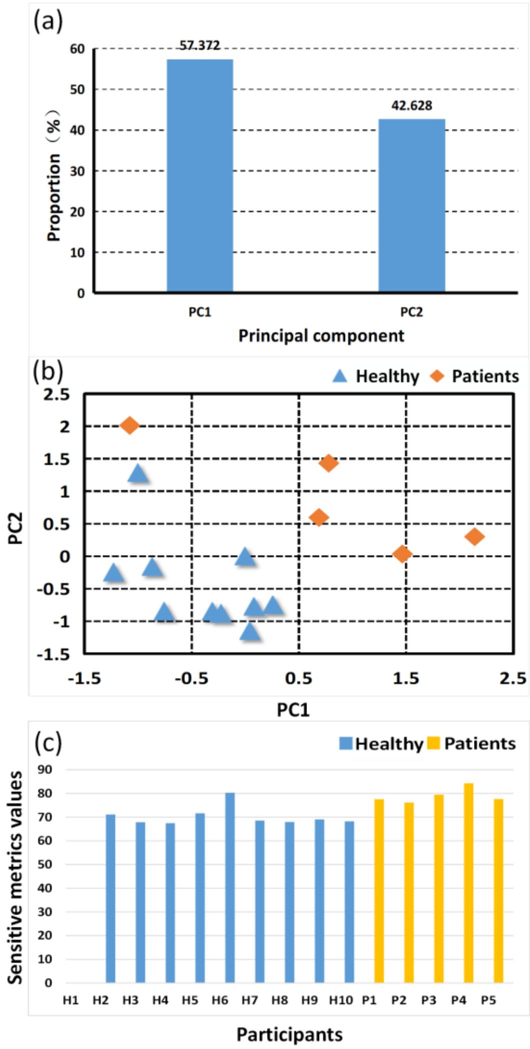

Fig.6. (a) PCA method's results of Thumb; (b) principal component analysis of Thumb, and (c) the significance analysis of the index.

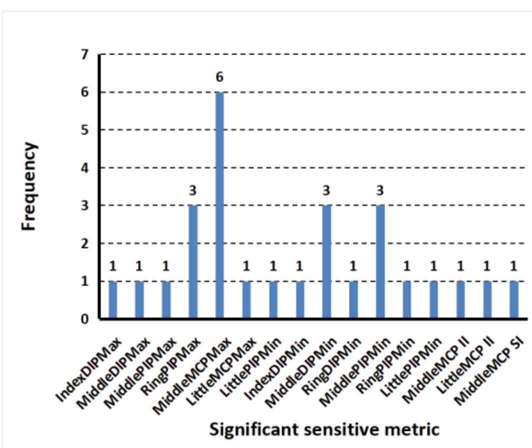

Fig.7. Significant sensitive metrics statistical diagram.

As described in Fig. 1, this study utilized various statistical methods, such as independent sample t-test, Mann-Whitney U test, and PCA (principal component analysis), to screen for sensitive kinematic metrics. Its feasibility has been demonstrated in previous studies [14]. Furthermore, the effectiveness of utilizing sensitive metrics for functional assessment has been proven by M. Longhi et al. [15]. Thus, the proposed approach via using hand kinematic metrics to distinguish stroke patients from healthy individuals and aid in functional evaluation is innovative and practical.

According to the statistical results of each task, the most frequent occurrence in Task-I was MiddleMCP-Max, with a frequency of five times in total and a frequency share of 71%. All other metrics appeared only once. Task-II to VI can be interpreted as a fine-grained decomposition of Task-I. MiddleDIP-Min and MiddlePIP-Min appeared 3 times, RingPIP-Max appeared 2 times, and all the other metrics appeared only once (See TABLE. IV for detailed data). These findings suggested that the middle was the most sensitive kinematic metric for the six functional tasks.

Additionally, it can be seen from the results that all three joint angles of the middle were screened with high frequency, and the number of occurrences of the sensitive metrics of the middle accounted for 59.3% of the total sensitive metrics, which further emphasized the importance of the sensitive metrics of the middle. Regarding the middle, MiddleMCP-Max was used as the most important kinematic metric, and MiddleDIP-Min & MiddlePIP-Min can be used as supplementary factors. In conclusion, the most kinematic metric of the hand was MiddleMCP-Max, which can effectively distinguish patients from normal individuals and assist in the clinical assessment of stroke hemiplegia.

This study has employed rigorous methods such as data validation, statistical analysis, and comparison experiments with healthy individuals and patients, making its conclusions scientifically objective. However, some limitations need to be acknowledged: a) due to the limited experimental time, the number of patients collected is not enough; b) the potential impact of patient gender on the experimental results was not considered; c) the number of selected kinematic metrics is limited, only involving angular kinematics and other types of kinematics; d) additional training and learning for more advanced programming methods are needed. Although the study suggests that the angular kinematic metric of the middle is the most sensitive, further research with larger sample sizes and more various kinematic metrics is necessary to confirm its generalizability.

V. Conclusion

This study aimed to assess hand function in stroke patients by analyzing movement data and selecting 38 metrics from both angular and other kinematic perspectives to identify sensitive and distinguishable metrics. Statistical methods, such as the normal distribution, independent sample T-test, and Mann-Whitney U-test, were used to screen out sensitive metrics. The PCA method was used to analyze the selected metrics. Fifteen volunteers participated in the comparison experiment, and the results showed that MiddleMCP-Max was the most sensitive metric. Future endeavors will concentrate on two aspects to enhance the applicability of the findings: 1) involve a larger pool of healthy participants and stroke patients in subsequent experiments, and 2) validate the efficacy of the assessment method via clinical applications.

TABLE. IV STATISTICAL ANALYSIS OF SENSITIVE METRICS FOR ALL TASKS

Task	Metric1(ID)	Metric2(ID)	Metric3(ID)	Metric4(ID)	Metric5(ID)	Metric6(ID)
Task-I (Thumb)	MiddleMCP-Max (0.074)	LittlePIP-Min (**0.977**)	N/A	N/A	N/A	N/A
Task-I (Index)*	MiddleMCP-Max	N/A	N/A	N/A	N/A	N/A
Task-I (Middle)	RingPIP-Max (**0.964**)	MiddleMCP-Max (0.266)	N/A	N/A	N/A	N/A
Task-I (Ring)*	MiddleMCP-Max	N/A	N/A	N/A	N/A	N/A
Task-I (Pinky)*	MiddleMCP-Max	N/A	N/A	N/A	N/A	N/A
Task-II (Thumb)	MiddleMCP-Max (-0.559)	MiddleDIP-Min (0.326)	MiddlePIP-Min (0.328)	MiddleMCP-II (-0.775)	MiddleMCP-SI (**0.882**)	N/A
Task-III (Index)	IndexDIP-Max (-0.073)	MiddlePIP-Max (0.535)	RingPIP-Max (**0.877**)	MiddleDIP-Min (0.816)	MiddlePIP-Min (0.611)	N/A
Task-IV (Middle)	MiddleDIP-Max (-0.407)	RingPIP-Max (0.233)	MiddleDIP-Min (**0.872**)	RingDIP-Min (0.439)	RingPIP-Min (0.859)	LittlePIP-Min (0.787)
Task-V (Ring)	LittleMCP-Max (0.489)	LittleMCP-II (**0.872**)	N/A	N/A	N/A	N/A
Task-VI (Pinky)	IndexDIP-Min (0.303)	MiddlePIP-Min (**0.953**)	N/A	N/A	N/A	N/A

*Task-I (Index, Middle, Pinky) is unable to perform the PCA method as only one sensitive metric was selected.

*Metric interpretation: for example, MiddleMCP-Max refers to the maximum angle of the metacarpophalangeal joint of the middle; LittleMCP-II refers to the II vaule of the metacarpophalangeal joint of the little; MiddleMCP-SI refers to the SI value of the metacarpophalangeal joint of the middle.

*The values in parentheses indicate the proportion of each sensitive metric in the first principal component (PC1).

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