

Classification of Hand-Movement Disabilities in Parkinson’s Disease Using a Motion-Capture Device and Machine Learning

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INTRODUCTION

Parkinson's disease (PD) is a rapidly growing neurodegenerative disease worldwide. PD patients have symptoms that affect both motor and non-motor aspects of daily life [1]. Motor symptoms are important clues in the diagnosis [2, 3]. The Movement Disorder Society Unified Parkinson’s Disease Rating Scale (MDS-UPDRS) is the standard tool for evaluating PD symptoms, part III of which is specific to motor symptoms [4]. In this part, the doctor visually observes the patient's movements and evaluates the severity on a five-point scale from 0 (normal) to 4 (severe). **However, this approach requires a specialist skilled in the MDS-UPDRS and results in variability in evaluation among diagnosticians [5].**

Sensor-based devices designed for quantitative kinematic measurement of limb movements have recently become readily available. These devices include wearable sensors, accelerometers, gyroscopes, and camera-based sensors, **but they might not be suitable for practical application due to size, cost, and time requirements.**

PURPOSE

To overcome these challenges, we proposed a Machine learning (ML) model that can evaluate motor symptoms using inexpensive sensors. ML-based methods have emerged as robust approaches for identifying complex data patterns, automating data analysis, and making inferences/classifications related to diseases, including PD [6, 7]. Given that the rating of motor symptoms predominantly involved assessing kinematic characteristics, the integration of sensor-based devices and ML-based techniques hold the potential to outperform human experts in symptom evaluations.

METHODOLOGY

Data Collection

This study used the Leap Motion device (LMD) to quantitatively measure and analyze hand movements [8]. LMD has several key advantages, including compact size, affordability, high resolution image acquisition, and minimal need for markers or devices on subjects during data collection. Therefore, LMD is suitable for the quantitative assessment of motor symptoms. This study selected 45 PD patients to perform three hand-related tasks from the MDS-UPDRS part III: finger tapping (FT), hand opening and closing (OC), and forearm pronation and supination (PS). LMD recorded these tasks and supplies time-series data, including finger joint positions and the orientation of the palm.

Data Analysis

We extracted features not only from the task-related movements but also from the movements of other joints. Raw data were extracted 31 movement patterns for each task as shown in Fig. 2 and Table 1. For the FT task, we calculated two task-related movement patterns: (i) FTdis represents the Euclidean distance between the index finger and thumb, and (ii) FTang represents the angle formed between the index finger and thumb. From these movement patterns, the extreme values of the area where the task was performed and detected which was used for feature extraction (Fig. 3). Then, 69 statistical features were extracted from each movement pattern, yielding 2139 features for each task as shown in Fig. 4.

Feature Selection

Two feature selection methods employed to identify significant features for PD patients. We initially employed Random Forest (RF) to select the top 15% of features (321 features) using Gini impurity. Then, these selected features were subsequently fed into a sequential-forward-floating-selection (SFFS) with support vector machine (SVM) algorithm to identify the relevant combination of features using classification accuracy which was used for predicting the severity of PD patients.

RESULT and CONCLUSION

We trained an SVM model for predicting the severity of PD patients. We used LOOCV to train SFFS with the SVM model and fine-tuned the hyperparameters of SVM using Optuna. These tuning efforts were performed separately for the FT, OC, and PS tasks. During the training phase, we systematically explored two kernel functions (RBF and sigmoid) and set the cost and γ to various values within the range from 0.01 to 100. Our approach involved conducting 200 trials with the seed value fixed at 42. Our observations revealed that SFFS with an SVM algorithm yielded the highest classification accuracy of **87.0% for FT, 93.2% for OC, and 92.2% for PS, which was comparatively higher than that achieved in the study of Chen et al. [9]. We anticipate that this proposed system will prove invaluable to physicians in assessing motor symptoms in PD patients.**

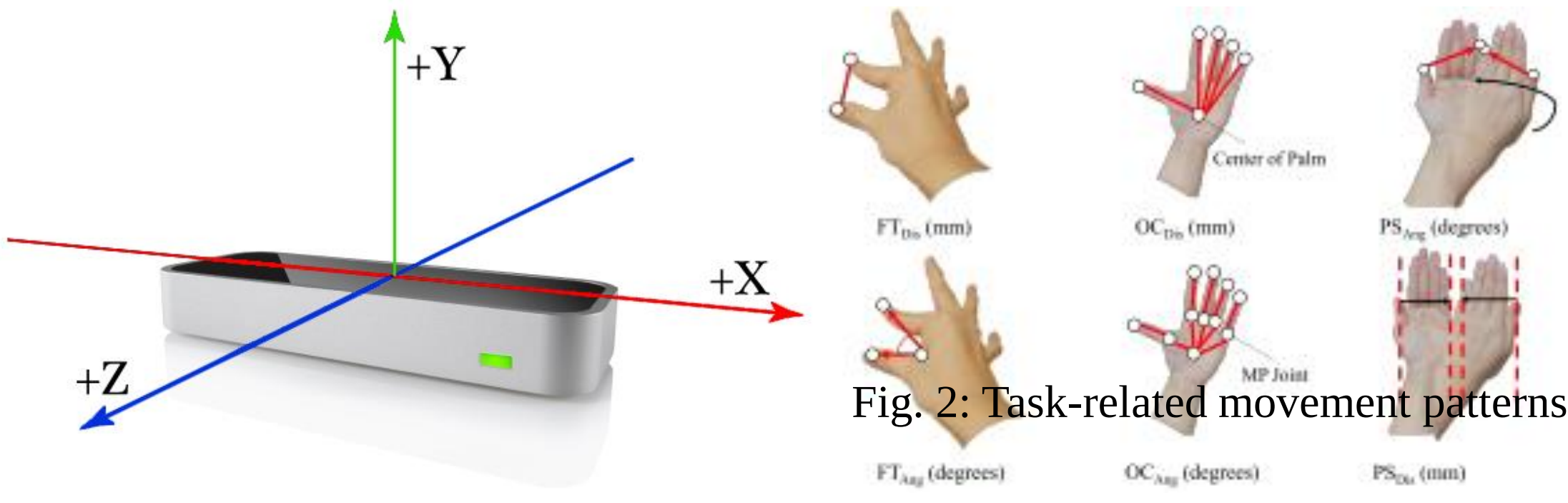


Fig. 1: Leap Motion Device

Table 1: Names and explanations of other extracted movement patterns

Name of movement pattern	Description
Palm2(Thumb, Index, Middle, Ring, Little)	Distance from the palm position to the tip of the (thumb, index, middle, ring, little) finger.
Thumb2(Index, Middle, Ring, Little)	Distance from the tip of the thumb to the tip of the (index, middle, ring, little) finger.
Index2(Middle, Ring, Little)	Distance from the tip of the index finger to the tip of the (middle, ring, little) finger.
Middle2(Ring, Little)	Distance from the tip of the middle finger to the tip of the (ring, little) finger.
Ring2Little	Distance from the tip of the ring finger to the tip of the little finger.
Thumb_IP	Range of motion the interphalangeal joint
(Index,Middle, Ring, Little)_DIP	Range of motion the distal interphalangeal joint
(Index,Middle, Ring, Little)_PIP	Range of motion the proximal interphalangeal joint
(Thumb, Index, Middle, Ring, Little)_MP	Range of motion the metacarpophalangeal joint

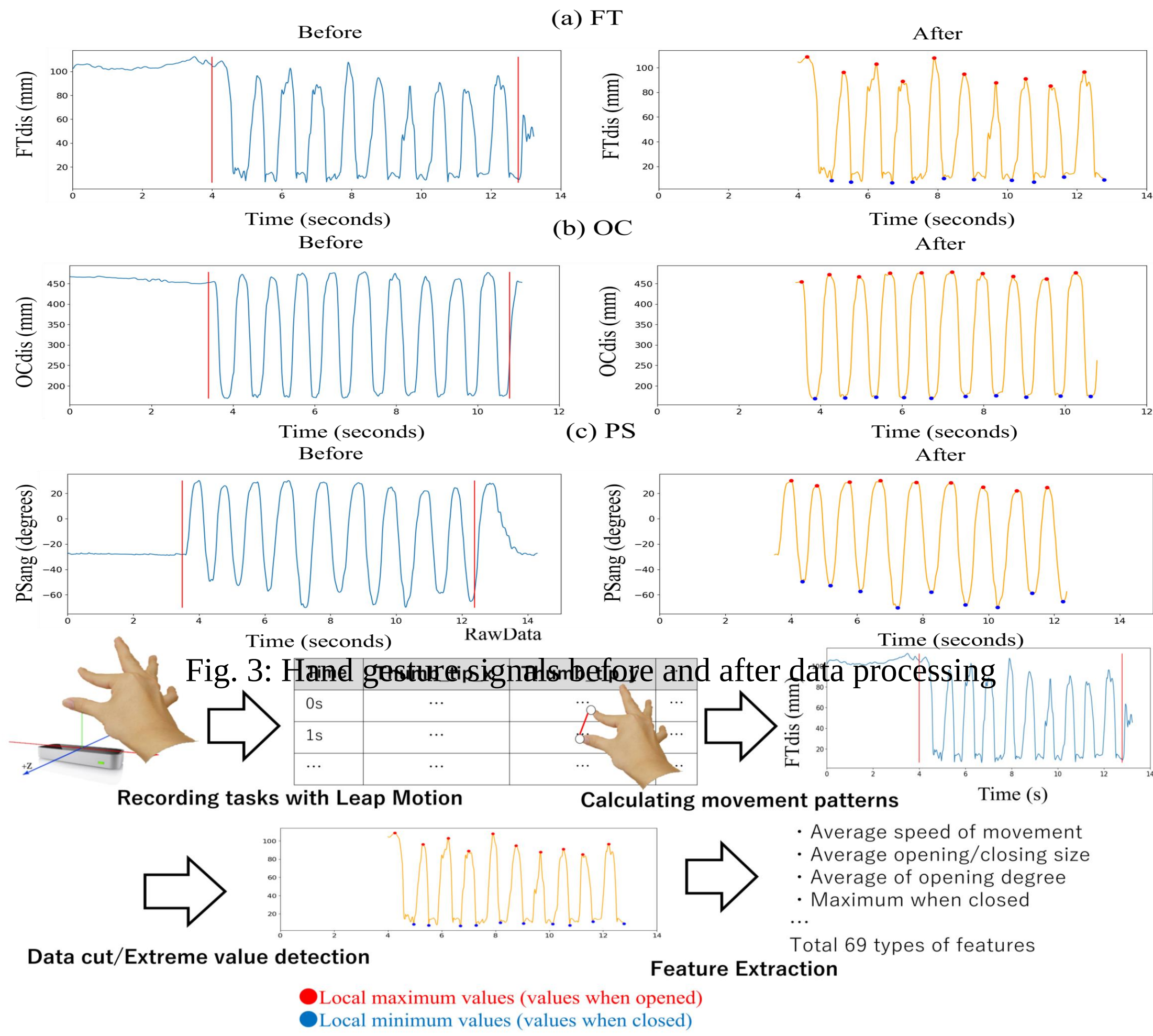


Fig. 4: Flowchart of feature extraction for FTdis

Table 2: Classification performance scores (in %)

Tasks	Accuracy	Precision	Recall	F1-score
FT	87.0	89.5	83.3	85.9
OC	93.2	76.1	73.2	74.4
PS	92.2	74.0	74.0	73.9

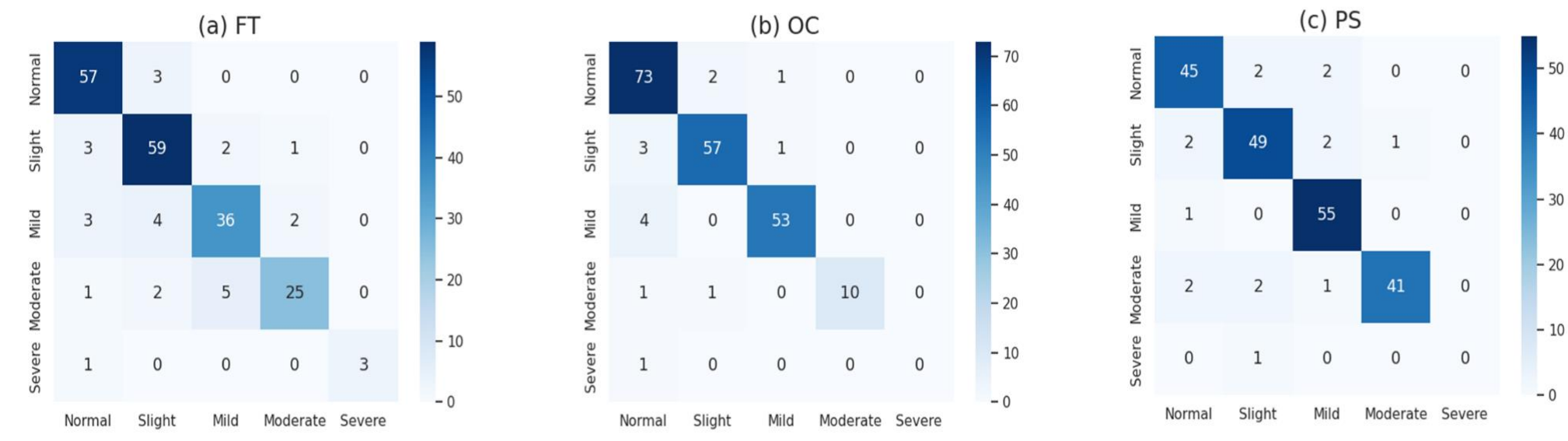


Fig. 5: Confusion matrix for three tasks: (a) FT; (b) OC; and (c) PS.

Table 3: Comparison of our study with other work

Ref.	Device	Task	Target & Class	Classifier	Accuracy (%)
Chen [9]	Video	FT, OC, PS	UPDRS score & 5 class	RF	FT: 85.7 OC: 89.3 PS: 88.6
Our study	Leap Motion	FT, OC, PS	UPDRS score & 5 class	SVM	FT: 87.0 OC: 93.2 PS: 92.2

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