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Quantification of Parkinsonian Bradykinesia Based on Axis-Angle Representation and SVM Multiclass Classification Method

ZHIRONG LIN[1], YONGSHENG XIONG[1], GUOEN CAI[2], HOUDE DAI[1], XUKE XIA[1], YANDAN TAN[1], AND TIM C. LUETH[3], (Member, IEEE)
[1]Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences, Jinjiang 362200, China
[2]Department of Neurology, Affiliated Union Hospital of Fujian Medical University, Fuzhou 350001, China
[3]Institute of Micro Technology and Medical Device Technology, Technical University of Munich, 85748 Garching, Germany

Corresponding author: Houde Dai (dhd@fjirsm.ac.cn)

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ABSTRACT Accurate evaluation of bradykinesia plays a crucial role in the diagnosis and therapy effect of Parkinson's disease. However, the subjective assessment shows low consistency among different evaluators, and the objective sensor-based methods cannot accurately distinguish patients with different grades of the 5-point clinical bradykinesia ratings. In this paper, an objective scoring method based on axis-angle representation and multi-class support vector machine (SVM) classifier was employed to estimate the bradykinesia severity. To reduce the dimension of attitude data for the better statistical analysis, the axis-angle representation approach was employed to obtain the 1- D combined orientation angle to express the 3-D hand-grasping assessment task. The significant bradykinesia features extracted from the 1-D combined orientation angle were used to train the SVM classification algorithm to acquire an objective score on the bradykinesia severity. Clinical experiments with 78 patients and 18 age-matched healthy subjects showed that the classification accuracy of the proposed method was 95.349%, which was superior to other related reports. Hence, the proposed objective scoring method can provide a 5-point bradykinesia score in real-time, and matches the clinical assessment approach of neurologists. Moreover, this method improves both the inter-rater reliability and intra-rater reliability of the bradykinesia assessment.

INDEX TERMS Parkinsonian bradykinesia, support vector machine (SVM), quantification, wearable device, sensor fusion.

I. INTRODUCTION

Parkinson's disease (PD) is a common neurodegenerative disease, which affects approximately 1% of the population over 55 years old [1]. Rest tremor, bradykinesia, rigidity and postural instability are the primary clinical character of PD. Bradykinesia is defined as slowness of motion and occurs in almost every case of PD [1]. Moreover, bradykinesia causes difficulties in daily activities such as dressing, eating, and bathing [2], which can be made worse by emotional stress or intercurrent illnesses. Therefore, accurate and objective evaluation of bradykinesia occupies a pivotal part in the diagnosis and monitoring of PD.

The gold standard for clinical diagnosis of bradykinesia severity is the evaluation using the standard clinical rating scales, which is performed by the well-trained neurologists [3]. The most commonly used clinical rating system for PD is the Movement Disorders Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS), which ranges from 0 to 4 (0=normal, 1=slight, 2=mild, 3=moderate, 4=severe) [4]. In the motor examination (Part III) of MDS-UPDRS, a series of assessment tests are defined, including the finger tapping, rapid and repetitive hand-grasping movements, and pronation-supination movements, which are completed by the patients and the evaluators assess the movement performance according to the rating scales. However, the rating is a subjective assessment based on the personal experience and relies mainly on the visual judgment of neurologists, which shows low agreement among different evaluators. An objective and automatic scoring of the bradykinesia severity can eliminate inconsistencies and interrater assessment disagreements among different evaluators, so as to improve the evaluation and monitoring of PD symptoms.

The movement characteristics used to evaluate the bradykinesia in MDS-UPDRS consist of speed, amplitude, the occurrence of hesitations, and any variability or changes in these characteristics over time [4]. Given the wide application of wearable sensor technology and machine learning algorithms [5], some researchers started to try to develop systems that allow doctors to recognize these movement disorder characteristics in sensor-wearing patients remotely and objectively. In this direction, there have been a series of articles employing various wearable motion sensors or multiple-sensor combinations, such as accelerometers [6]–[8], gyroscopes [9]–[11], magnetic sensors [12], gyroscope-accelerometer combinations (IMUs) [13], [14], and attitude and heading reference systems (AHRS, composed of a triaxial gyroscope, a triaxial accelerometer, and a triaxial magnetic sensor) [15], [18].

Kim *et al.* [9] used a quantitative measurement system based on a gyroscope to recognize movement disorders of 40 PD patients during the finger tapping assessment test. Indices derived from the gyroscope signal showed high correlations with the clinical assessment results ($r=-0.73$ to -0.80, $p<0.001$). Salarian *et al.* [10] employed a gyroscope worn on the wrist to extract quantitative bradykinesia parameters in 20 PD patients. The clinical experiment results demonstrated that the extracted quantitative bradykinesia features, such as amplitude and periods of movements, correlated well with the UPDRS scores ($r=-0.83$, $p=0.001$). These studies focused on the extraction of related parameters of bradykinesia, which show significant correlation with the clinical evaluation. However, they cannot score directly on the severity of parkinsonian bradykinesia.

Applications of machine learning algorithms for objective monitoring and assessment of PD have attracted considerable attention during recent years. Several notable researches based on machine learning algorithms were reported. Patel *et al.* [8] used a support vector machine (SVM) classifier to identify patients with Parkinsonian bradykinesia from accelerometer data. Based on the inertial and electromyographic signal, Rabelo *et al.* [16] employed the k-nearest neighbor (KNN) classifier to discriminate patients with parkinsonian bradykinesia from healthy aged people. The mean specificity and sensitivity in discriminating patients and healthy aged were 83.33% and 86.67% respectively. In addition, Arora *et al.* [17] used random forests to distinguish PD patients from healthy people based on a broad variety of smartphone sensor data. The experiment results with 20 participants showed that the mean sensitivity and specificity were 96.2% and 96.9% respectively. In spite of good results, most of these classification methods focused on the diagnosis: discriminating between healthy and PD cases, which cannot directly distinguish patients with different grades of UPDRS bradykinesia score.

Trying to overcome the limitations of the subjective diagnosis, Martinez-Manzanera *et al.* [18] used an AHRS and an SVM-based classification method to obtain automatic scores of three bradykinesia-related movements (finger tapping, diadochokinesis and toe-tapping) of 25 PD patients. A quaternions-based fusion algorithm was employed to obtain the three-dimensional (3D) representation of movements. In [18], quantitative features were extracted from a single Euler angle, which explains most of the hand motion and can be named the dominant axis. The dominant axis for each assessing task was defined before the assessment. However, a single Euler angle cannot provide full information of the assessing movement, and the selected dominant axis may vary to other two axes during the assessment task, which will deteriorate the classification accuracy of the bradykinesia severity.

In this study, the axis-angle representation approach was employed to replace the single Euler angle to describe the hand-grasping assessment movement based on the full 3D information. The nine degrees-of-freedom (9DoF) sensor fusion algorithm based on Kalman filter was used to obtain the 1D combined orientation angle of hand-grasping movement. Features closely related to the significant bradykinesia characteristics (speed, amplitude, and variability) were extracted from the 1D combined orientation signal to train the SVM multiclass classifier for estimating the bradykinesia severity. The proposed objective scoring method can assess the MDS-UPDRS bradykinesia-related items to reproduce the classification results (5-point bradykinesia score: 0-4) of the evaluators. The main contribution of our study is that the axis-angle representation method was applied to obtain the 1D combined orientation angle, which can replace the Euler angle to express the full 3D information of hand-grasping assessment task. In accordance with the clinical UPDRS assessment method, the SVM-based multiclass classification can score the severity of bradykinesia to reproduce the evaluators' classification results with superior classification accuracy. In addition, the objective scoring method proposed in our study was compared with the other supervised classification algorithm, like the KNN classifier.

II. METHODS

A. SUBJECTS AND EXPERIMENT DESIGN

78 patients with slight to severe PD (UPDRS bradykinesia score: 1-4) and 18 age-matched healthy controls (UPDRS bradykinesia score: 0) participated in the clinical experiments. Their demographics are listed in Table 1. The participants were separated into two groups: one group (43 PD and 10 controls) was used as the training set to train the learning algorithm, and the other group (35 PD and 8 controls) was used as the testing set for testing the algorithm. The distributions of the training and testing samples are listed in Table 2. The division of participants demonstrated that the proposed classification methods are

TABLE 1. Participants' demographics.

Demographics	*Patients*	*Controls*
number	n=78	n=18
Age (years)	65.32±10.72	62.8±5.94
Males/Females	51 M/27 F	11 M/7 F
Disease duration (years)	6.96±3.34	-

TABLE 2. The distribution of dataset.

UPDRS bradykinesia score	*Training set*	*Testing set*
0	n=10	n=8
1	n=18	n=14
2	n=17	n=14
3	n=6	n=5
4	n=2	n=2

subject-independent and do not require pre-training for each application. According to the MDS-UPDRS, the rapid and repetitive hand-grasping task (Item 3.5 in the MDS-UPDRS) was adopted in this study to evaluate the severity of parkinsonian bradykinesia. A single closing and opening action of the hand is considered as a grasp cycle. All participants were instructed to open the hand as fast and as fully as possible for 10 seconds. For every participant, the assessment task was videoed and later scored by an experienced neurologist according to the MDS-UPDRS criterion. The controls are healthy and age-matched participants who are reported no movement disorder or any other neurological diseases. Patients were told to stop medication at least 12 hours before the experiments to make sure they were assessed in OFF-levodopa state.

All clinical experiments were completed at the Affiliated Union Hospital of Fujian Medical University (Fuzhou, China). This study was approved by the Ethics Committee of Affiliated Union Hospital of Fujian Medical University.

B. SYSTEM FOR SIGNAL ACQUISITION

As Fig. 1 shows, a custom wearable device was developed for signal acquisition. The wearable device involves a fingertip unit, which consists of a consumer-grade AHRS (BNO055, Bosch Sensortec GmbH, Germany), a wrist-worn microcontroller board (MCU; ATmega1284P, Atmel Inc., USA) and a Wireless Fidelity (WiFi) module (ESP-8266, Espressif Systems Pte., Ltd., China). The AHRS was worn on the fingertip of the forefinger to capture the finger's activity. Before each measurement, the AHRS was calibrated by using the calibration algorithm provided by the Bosch Sensortec GmbH. The ranges of the three individual sensor components are ±4g, ±2000°/s, and $+/-1300\mu$T respectively. After fusing data from the three individual sensor components, the AHRS output, involving quaternion, Euler angles, rotation vector, linear acceleration vector, gravity vector, are acquired.

The AHRS outputs were sampled at 100Hz and transmitted from the wearable device to the computer via WiFi in

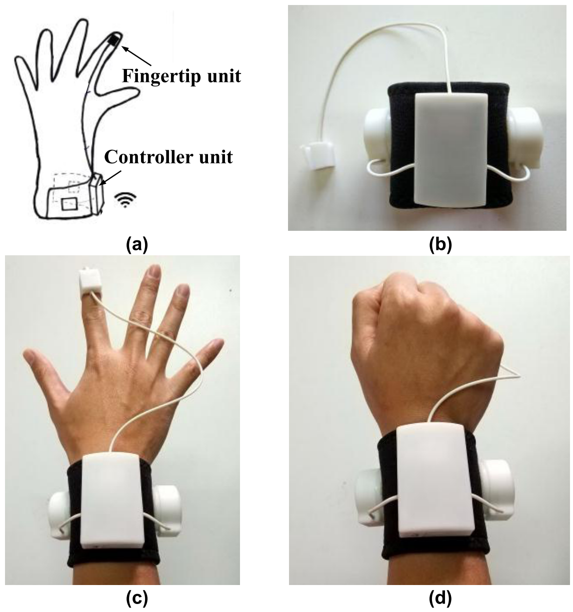

FIGURE 1. The proposed bradykinesia quantification system. (a) system diagram; (b) prototype implementation; (c) the starting posture of a hand-grasping cycle; (d) the end posture of a hand-grasping cycle.

real-time. Then the AHRS outputs were saved for offline analysis by using MATLAB R2014a (Mathworks Inc., USA).

C. SENSOR FUSION AND FEATURES EXTRACTION

To acquire a more accurate hand-grasping angular displacement, signals from the AHRS were fused with the Kalman filter theory, which is regarded as the most popular probabilistic fusion algorithm applied in high-precision motion tracking [19].

Fig. 2 illustrates the diagram of the Kalman filter-based sensor fusion, which is an iterative process. The Kalman gain, which depends on the covariance terms and varied in real-time, represents the weight factors of the K and K-1 parameters. The covariance values are determined by the models of each sensor's total noise. In addition, other impact factors for long-term drift, such as temperature drift, linear acceleration, and vibration were used to optimize the covariance values. To overcome the disadvantages (gimbal lock) of traditional Euler angles, the sensor fusion method utilized quaternions to represent the orientations. A quaternion is a 4D complex

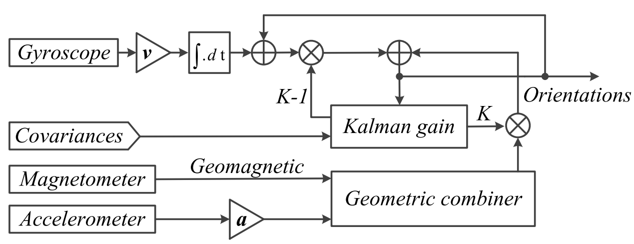

FIGURE 2. Block diagram of the Kalman filter for orientation estimation. ***a*** represents the acceleration vector, ***v*** represents the angular velocity vector. K-1 and K are the time series.

number that can be used to represent the orientation of a rigid body or coordinate frame in 3D space.

According to the axis-angle representation method [20], the orientation of a rigid body in a 3D Euclidean space can be equivalent to rotating a certain angle around a rotating axis. Assuming the direction vector of the equivalent rotation axis is $\vec{\boldsymbol{K}} = \left(k_x, k_y, k_z\right)^{\mathrm{T}}$ and the equivalent rotation angle is θ, the quaternion $\boldsymbol{q}$ can be written as follows:

$$\boldsymbol{q} = \begin{bmatrix} q_1 & q_2 & q_3 & q_4 \end{bmatrix}. \tag{1}$$

Here,

$$\begin{cases} q_1 = k_x \cdot \sin(\theta/2) \\ q_2 = k_y \cdot \sin(\theta/2) \\ q_3 = k_z \cdot \sin(\theta/2) \\ q_4 = \cos(\theta/2) \\ q_1^2 + q_2^2 + q_3^2 + q_4^2 = 1. \end{cases} \tag{2}$$

The quaternion contains the information of the rotation axis and rotation angle, which can conveniently describe the rotation of the rigid body around an arbitrary axis.

The hand motion during the hand-grasping task can be described by a single-axis combined orientation angle, which depicts the flexion and extension of the palm. Therefore, to reduce the dimension of attitude data for the better statistical analysis, the axis-angle representation method [20] was employed to obtain the 1D combined orientation angle to express the 3D hand grasping motion. The 1D combined orientation angle, i.e., the equivalent rotation angle θ, can be formulated as follows:

$$\theta = 2\arccos(q_4), \tag{3}$$

where the single-axis combined orientation angle θ ranges from 0 to 180°.

To obtain features which are closely related to the significant bradykinesia characteristics assessed in the MDS-UPDRS (e.g., speed, amplitude, and the variability), we defined three characteristic parameters to describe the movement disorders during the hand movements. Firstly, the dominant frequency (f) of hand-grasping movement was adopted to represent the speed of movement, which was computed based on the number of the hand-grasping cycles (N) during the 10-second assessment period:

$$f = N/10. \tag{4}$$

The orientation angle θ represents the hand-grasping range in bradykinesia assessment task, and the grasping amplitude was obtained from the mean value ($\bar{\varphi}$) of peak-to-peak angles:

$$\overline{\varphi} = \sum_{i=1}^{N} |\theta_{\max} - \theta_{\min}|_i / N, \tag{5}$$

where $\theta_{\max}$ and $\theta_{\min}$ represent the peak and valley values of the orientation angle in the i-th grasp cycle.

In this study, a peak detection method [21] was adopted to acquire the peak-to-peak values of grasping range φ. By proceeding the angle signal starting from zero, the peak detection method found the maximum and minimum values of the hand-grasping range. To describe the variability of amplitude during the hand-grasping movement, the standard deviation (SD) value of grasping ranges was adopted:

$$\sigma_{|\varphi|} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(\overline{\varphi} - |\varphi|_i\right)^2}, \tag{6}$$

where $|\varphi|_i$ is the peak-to-peak angle in the i-th grasp cycle; N represents the number of the hand-grasping cycles in 10s' assessment task.

D. STATISTICAL ANALYSIS

To verify the effectiveness of the three bradykinesia-related features, the statistical analysis was carried out for each characteristic parameter. The one-way ANOVA (analysis of variance) test was employed to analyze the difference of each parameter between different UPDRS bradykinesia grades. In addition, the Pearson correlation analysis was examined to determine the relation of data in each parameter and the UPDRS bradykinesia scores. All the p values in this study were two-sided tests, and $p<0.05$ was considered to be statistically significant. All statistical analyses were completed by using SPSS ver.22 (SPSS Inc., Chicago, IL, USA).

E. MULTICLASS CLASSIFICATION ALGORITHM

We employed SVM-based classifier for the automatic classification to objectively evaluate the severity of parkinsonian bradykinesia. A classification problem includes dividing the dataset into training and testing sets (as Table 2 shows). In the training set, each case includes one target value (i.e., the class labels) and several attributes (i.e., the features). The SVM was designed to obtain a classification model, which can predict the class labels of the test instances where only the features were given.

SVM is a supervised learning model which can be used for classification and regression analysis. The features are mapped by a kernel function to a higher dimensional feature space where data can be distinguished by a hyperplane. Almost every feature extracted from data can be involved in an SVM classifier, but this might lead to over-fitting and poor performance because of the curse of dimensionality [22]. Thus, to obtain satisfactory classification results, the classification in this study was based on features (dominant frequency f, mean grasping angle $\bar{\varphi}$, and standard deviation of grasping ranges $\sigma_{|\varphi|}$) highly related to the significant movement disorder characteristics (speed, amplitude, and their variability) assessed in the MDS-UPDRS.

SVM was initially designed for binary classification, whereas the bradykinesia severity was scored on a 5-point scale (bradykinesia scores: 0-4) according to the MDS-UPDRS criteria by an experienced neurologist in this study. Therefore, the traditional SVM classification needs to extend to handle the multiclass problem. From some SVM-based methods that were applied for multiclass classification [23], a one-against-all strategy (e.g., score-zero versus the rest of the classes) based on the binary classification was selected for distinguishing patients with different grades of UPDRS bradykinesia score. For each SVM binary classifier, given an instance-label pair from the training set (x_i, y_i), $i = 1, 2, \ldots, l$ where $x_i \in \mathrm{R}^n$ and $y_i \in \{1, -1\}^1$, and the SVM classification was designed to solve the following optimization problem [24]:

$$\begin{aligned} &\min_{\mathbf{w},b,\xi} \ \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i \\ &\textit{subject to } y_i(\mathbf{w}^T\phi(x_i) + b) \geq 1 - \xi_i \\ &\qquad\qquad \xi_i \geq 0, \end{aligned} \tag{7}$$

where $\mathbf{w}$ is the weights vector of the optimal hyperplane, ξ_i is a non-negative variable which equals to $\max(0, 1 - y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b))$, and b is a constant. C is the penalty parameter, and $\mathbf{x}_i$ are mapped to a higher dimensional feature space by the function ϕ.

In the one-against-all classification method, the features in the testing set were used as the test sample of each SVM binary classifier to predict the class labels. The confidence value of each test instance was determined by its position in the feature space, which can be represented by the Euclidian distance of the test sample to the separating hyperplane. The testing sample was then classified in the class obtained the highest confidence value across all SVM binary sub-classifiers. The separation boundaries of different classes in SVM were determined by choice of the appropriate kernel function. As a reasonable first choice in SVM [25], we adopted the radial basis function (RBF) kernel as follows:

$$K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2), \quad \gamma > 0, \tag{8}$$

where γ is the kernel parameter, which represents the influence of the squared Euclidian on building the hyperplane.

We employed the cross-validation and grid-search method [25] to determine the optimal kernel parameter γ and penalty parameter C.Several different pairs of (C, γ) values were tried in the SVM model and the one achieved the highest cross-validation accuracy was adopted. In this study, γ and C were adjusted to 0.2 and 1.5 respectively. In addition, to avoid poor classification performance, the z-scores method was used to normalize all the features.

We used the classification accuracy as the evaluation criterion on the performance of a classifier. The classification accuracy was defined as the percentage of participants that are correctly classified (according to the clinical bradykinesia scores) in the testing set. The MDS-UPDRS bradykinesia scores from an experienced evaluator were used as the actual class labels of participants.

III. CLINICAL EXPERIMENT RESULTS

The custom bradykinesia quantification system successfully captured motion data from all participants (including training and testing sets) as they performed the clinical hand-grasping assessment task to evaluate the severity of parkinsonian bradykinesia.

Fig. 3 shows the hand-grasping angle waveform of the 10s assessment task for a PD patient and a healthy subject respectively. It is obvious that the frequency and amplitude of this PD patient's hand-grasping movement are much lower than those of the healthy subject. Moreover, the variability of grasping amplitude is different between the PD patient and healthy subject.

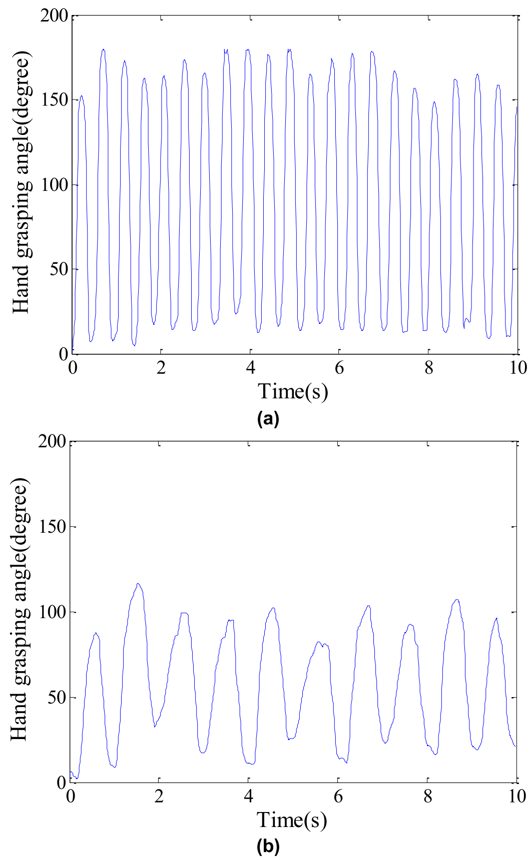

FIGURE 3. **Angle waveform of hand-grasping movement. (a) 68-year-old healthy control; (b) 67-years-old PD patient with UPDRS bradykinesia score=3.**

Fig 4 shows the descriptive statistics results for the three characteristic parameters. As can be seen from Fig. 4, compared with the standard deviation of grasping ranges $\sigma_{|\varphi|}$, the dominant frequency f and mean grasping angle $\bar{\varphi}$ show more significant difference among the five UPDRS groups. In addition, we utilized the one-way ANOVA test to analyze the differences of each characteristic parameter between different grades of UPDRS bradykinesia score. Table 3 shows the F values of the variance analysis and the corresponding significance level p values of the ANOVA in the training set. Apparently, it can be seen that the three characteristic parameters all show a significant difference among the five UPDRS grades (p<0.05). The F value of the dominant frequency f is the largest of all parameters, which indicates the difference of this parameter is the biggest. Table 4 describes the

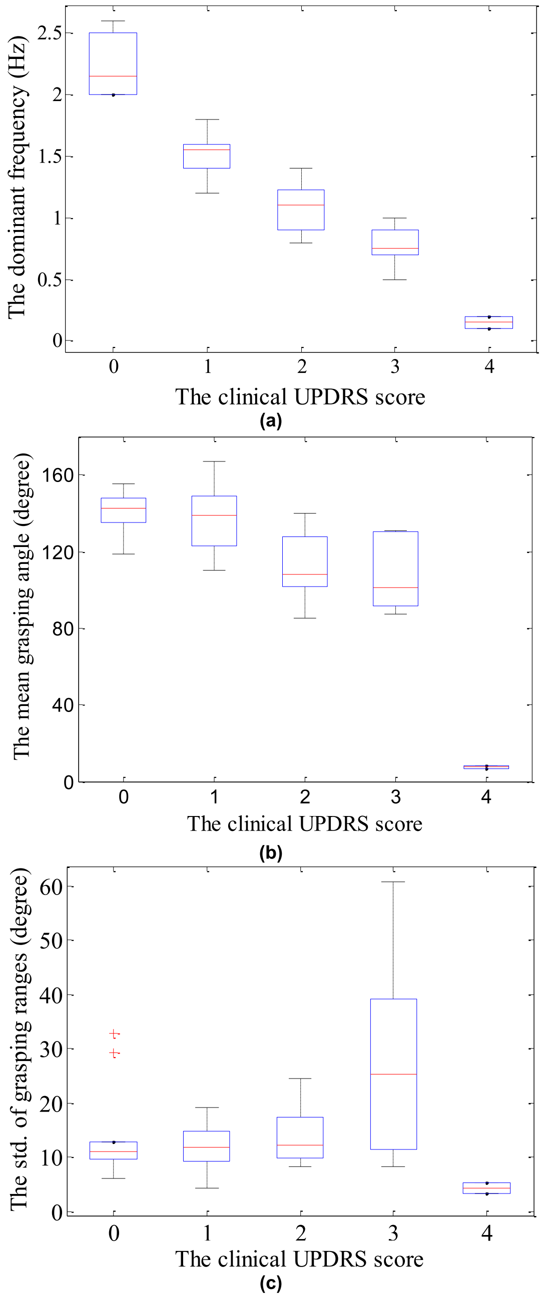

FIGURE 4. Box plots for summarizing the descriptive statistics results for the three characteristic parameters. (a) The clinical UPDRS score versus dominant frequency f; (b) The clinical UPDRS score versus mean grasping angle $\bar{\varphi}$; (c) The clinical UPDRS score versus standard deviation of grasping ranges $\sigma_{|\varphi|}$.

correlation between each characteristic parameter and the clinical assessment results. From the Pearson correlation coefficients r and corresponding p values, it can be seen that the dominant frequency f and grasping amplitude $\bar{\varphi}$ show significant linear correlation relationship with the MDS-UPDRS bradykinesia score (p<0.05). In spite of the nonlinearity with characteristic parameter $\sigma_{|\varphi|}$(r=0.312), the RBF kernel in SVM can nonlinearly map samples into a higher dimensional feature space, hence it can deal with the case when the relationship between classes and features is nonlinear.

TABLE 3. Results of single factor variance analysis.

Parameters		f	$\bar{\varphi}$	$\sigma_{\lvert\varphi\rvert}$
	Group 1	2.24±0.25	141.11±11.65	14.51±8.96
	Group 2	1.52±0.20	136.12±16.67	11.94±3.96
Mean±std	Group 3	1.09±0.17	114.20±16.94	13.91±5.02
	Group 4	0.77±0.18	107.04±18.98	28.38±19.76
	Group 5	0.15±0.07	7.62±1.12	4.36±1.35
F		93.055	34.806	5.327
p		<0.001	<0.001	0.02

TABLE 4. Results of the Pearson correlation analysis.

Parameters	f	$\bar{\varphi}$	$\sigma_{\lvert\varphi\rvert}$
r	-0.925	-0.715	0.312
p	<0.001	<0.001	0.028

The dominant frequency f, mean grasping angle $\bar{\varphi}$, and standard deviation of grasping ranges $\sigma_{|\varphi|}$ were chosen as features to train the classification algorithm. The chosen features were closely related to the important movement disorder characteristics (speed, amplitude, and variability), which were assessed in the MDS-UPDRS. The features and class labels in training set were used to train the classification model, and the classification performance was analyzed based on the testing set. Table 5 shows the confusion matrix of the classification results. Each column in the confusion matrix represents the test samples with a predicted class labels, and each row represents the test samples in an actual class. The main diagonal elements of the confusion matrix denote the numbers that correct decisions can be made. Classification results in Table 5 show that only two participants are incorrectly classified, with the classification accuracy of 95.349% (41/43).

TABLE 5. Confusion matrix of the classification results.

Actual / *Predicted*	*Class 1 (Score-0)*	*Class 2 (Score-1)*	*Class 3 (Score-2)*	*Class 4 (Score-3)*	*Class 5 (Score-4)*
Class 1 (Score-0)	7	1	0	0	0
Class 2 (Score-1)	0	14	0	0	0
Class 3 (Score-2)	0	0	14	0	0
Class 4 (Score-3)	0	0	1	4	0
Class 5 (Score-4)	0	0	0	0	2

In the one-versus-all method, the classification consists of five SVM binary classifiers. To depict the performance of each binary classifier, Table 6 shows several evaluation indices related to the classification performance, involving the true positive rate (TPR), false positive rate (FPR), specificity, precision, and F1-score respectively. All the indices are calculated from the confusion matrix in Table 5. The high F1-scores (93.33%, 96.55%, 96.55%, 88.89%, and 100%) of

TABLE 6. Classification results for the five SVM binary classifiers.

	Classifier 1 (score-zero)	*Classifier 2 (score-one)*	*Classifier 3 (score-two)*	*Classifier 4 (score-three)*	*Classifier 5 (score-four)*
TPR	87.5%	100%	100%	80%	100%
FPR	0	3.45%	3.45%	0	0
Specificity	100%	96.55%	96.55%	100%	100%
Precision	100%	93.33%	93.33%	100%	100%
F1	93.33%	96.55%	96.55%	88.89%	100%

TPR represents the true positive rate; FPR represents the false positive rate.

the five sub-classifiers suggest that the classifiers produce satisfactory classification results for discriminating the severity of bradykinesia.

For comparative analysis, the KNN classifier [26] was employed to further analyze the classification performance of SVM. The training of KNN classifier is based on the data from the same training set. Table 7 shows the confusion matrix of the KNN classification results based on the same testing set. From the confusion matrix, we can find that eight participants were incorrectly classified. Therefore, the classification accuracy is 83.72% (36/43), which is much worse than that of SVM. The choice of K value is based on preliminary and empirical evaluations showed this value produces the best classification result. Here, K is set to 5.

TABLE 7. Confusion matrix of the KNN classification results.

Actual / *Predicted*	*Class 1 (Score-0)*	*Class 2 (Score-1)*	*Class 3 (Score-2)*	*Class 4 (Score-3)*	*Class 5 (Score-4)*
Class 1 (Score-0)	6	2	0	0	0
Class 2 (Score-1)	0	14	0	0	0
Class 3 (Score-2)	0	0	14	0	0
Class 4 (Score-3)	0	0	3	2	0
Class 5 (Score-4)	0	0	0	2	0

IV. DISCUSSION

The high-precision hand-grasping tracking and the quantification of the parkinsonian bradykinesia severity were conducted by a custom wearable device based on an AHRS and SVM-based multiclass classification. We adopted SVM due to its success in many classification problems. The sensor fusion algorithm based on Kalman filter was employed to accurately capture the hand movement information during the hand-grasping assessment task. The axis-angle representation approach was used to obtain the 1D combined orientation angle, which can replace the Euler angle to express the full 3D information of hand-grasping assessment task.

78 PD patients (UPDRS bradykinesia score: 1-4) and 18 age-matched healthy controls (UPDRS bradykinesia score: 0) were involved in this study. The classification based on features such as speed, amplitude, and variability, which were highly related to the significant movement disorder characteristics assessed in the MDS-UPDRS, achieved satisfactory classification accuracy (95.349%). The main advantage of this study is that the axis-angle representation approach was applied to capture the movement thoroughly with a 1D combined orientation angle to perform high-precision hand-grasping motion tracking, which can reduce the dimension of attitude data for the better statistical analysis. The significant bradykinesia-related features (e.g., speed, amplitude, and the variability) extracted from the 1D combined orientation angle were used to train the SVM multiclass classification algorithm for the bradykinesia severity scoring (bradykinesia score: 0-4), in accordance with the clinical assessment method. Moreover, the objective scoring method proposed in this study was compared with another supervised classification algorithm, i.e., the KNN classifier. Classification results with the same testing set showed that the classification accuracy of the SVM-based classification method was superior to the KNN method.

The objective scoring method employed in this study has several advantages over previous studies. As mentioned, the related works proposed in [8]–[10], [16]–[17] cannot directly distinguish patients with different grades of UPDRS bradykinesia score. Moreover, the quantitative analysis of the selected assessment tasks was performed on a single Euler angle signal which explains most of the hand motion and can be named the dominant axis. However, a single Euler angle cannot provide full 3D information of the assessing movement, and the selected dominant axis may vary to other two axes during the assessment task, which will deteriorate the classification accuracy of the bradykinesia severity. Different with the orientation representation in [18], the proposed objective scoring method used the axis-angle representation instead of Euler angles to obtain the 1D combined orientation angle of hand-grasping movement, which can express the full 3D motion information and reduce the dimension of attitude data for the better quantitative analysis. Due to the Kalman filter sensor fusion and SVM-based multiclass classification method, the classification based on features extracted from the 1D combined orientation angle signal obtained satisfactory classification performance (95.349%), which is superior to the other related classification method, such as in [18], whose classification accuracy is less than 80%.

For comparative analysis, we used the KNN classification method to distinguish the bradykinesia severity of the participants from the same testing set. The classification accuracy of this KNN algorithm is 83.72%, which is much worse than that of SVM-based classification approach. In KNN classification, a subject is classified according to the class most common among its k nearest neighbors. This "majority voting" classification approach has a drawback when the sample distribution of different classes is skewed [27]. That is, samples of a more frequent class tend to dominate the prediction class of the new subject, because they tend to be common among the k nearest neighbors due to their large number. In this study, the sample size with the UPDRS score=1 and 2 was relatively larger than other groups, which result in several new samples were incorrectly classified as 1 and 2. This phenomenon can be seen from the confusion matrix in Table 7. Therefore, the KNN is contaminated by the drawback of majority voting, whose classification accuracy is worse than the proposed SVM-based classification approach. Moreover, the classification performance of KNN is influenced by choice of K value, which is based on preliminary and empirical evaluations.

V. CONCLUSION

Aimed at an objective assessment of the parkinsonian bradykinesia severity, we proposed an automatic and objective scoring method for the quantification of the MDS-UPDRS bradykinesia-related items based on the 9DoF sensor fusion algorithm, the axis-angle representation approach, and the SVM multiclass classification method. The fusion algorithm provides 3D rotations of the hand-grasping task, and the axis-angle representation approach reduces the 3D rotations to 1D combined orientation angle with full motion information, thereby the statistical analysis is simplified. SVM-based multiclass classifier achieves a superior classification performance (classification accuracy: 95.349%) based on the features related to the key characteristics during the hand-grasping assessment task. The proposed objective scoring method can not only offer physicians effective help for an accurate assessment of the bradykinesia severity, but also serve as a self-monitor setting at home for the patients themselves. In the future, we will integrate quantifications of other parkinsonian motor symptoms into this wearable system.

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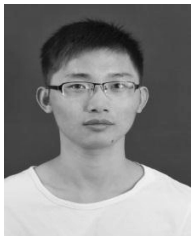
ZHIRONG LIN received the B.S. and M.S. degrees in signal and information processing from the University of Electronic Science and Technology of China in 2012 and 2015, respectively. He is currently a Research Assistant with the Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences, Quanzhou, China. His main research interests include sensor signal processing and quantitative assessment of Parkinson's disease.

YONGSHENG XIONG received the bachelor's degree in automation from the Zhengzhou University of Aeronautics in 2015. He is currently pursuing the master's degree in control engineering with the North University of China and the Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences, Quanzhou, China. His research interest is embedded software.

GUOEN CAI received the bachelor's degree in medicine from Fujian Medical University in 2005 and the M.S. degree in medicine from the Shanghai Jiao Tong University School of Medicine in 2008. He is currently a Attending Physician with the Affiliated Union Hospital of Fujian Medical University, Fuzhou, China.

HOUDE DAI received the B.Eng. degree in biomedical engineering from the University of South China, Hengyang, China, in 2005, the M.S. degree in biomedical engineering from Tongji University, Shanghai, China, in 2009, and the Ph.D. degree in mechanical engineering from the Technical University of Munich, Germany, in 2014. He is currently a Professor with the Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences, Quanzhou, China. His research interests include intelligent sensors, information processing, and mobile robots.



XUKE XIA received the B.S. and M.S. degrees in control engineering from the Anhui University of Science and Technology in 2013 and 2015, respectively. He is currently a Research Assistant with the Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences, Quanzhou, China. His research interest is embedded hardware.

YANDAN TAN received the bachelor's degree in educational technology from Shandong Normal University in 2017. She is currently pursuing the master's degree in control engineering with the North University of China and the Quanzhou Institute of Equipment Manufacturing, Haixi Institutes, Chinese Academy of Sciences, Quanzhou, China. Her research interest is biological signal processing.

TIM C. LUETH (M'89) received the Dipl.Ing. degree in electrical engineering from the Darmstadt University of Technology, Darmstadt, Germany, in 1989, and the Ph.D. degree in robotics and the Habilitation degree in computer science from the University of Karlsruhe, Karlsruhe, Germany, in 1993 and 1997, respectively. From 1994 to 1995, he was a Visiting Researcher with the MITI-AIST Electrotechnical Laboratory, Tsukuba, Japan. In 1997, he became a Professor of surgical navigation and robotics with the Medical School Charité-Universitätsmedizin Berlin, Humboldt University, Berlin, Germany. In 2001, he became the Director of mechatronic medical technology with the Fraunhofer Institute for Production Systems and Design Technology, Berlin. Since 2005, he has been a Professor, the Chair, and the Director with the Institute of Micro Technology and Medical Device Technology, Technical University of Munich, Germany. In 2006, he was a Professor with the University of Toronto, Toronto, ON, Canada.

He elected as a top three Inventors from the European Patent Office in the category of lifetime achievement for his patent activities in the area of surgical robotics and navigation in 2007. He received several national and international awards for his research on medical devices. In 2010, he became an Elected Member of acatech from the German National Academy for Science and Technology. He is an active member of the IEEE R&A Chapter and the IEEE Engineering in Medicine and Biology Society Chapter.