



# Monitoring motor symptoms in Parkinson's disease via instrumenting daily artifacts with inertia sensors

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## Abstract

Daily monitoring of Parkinson's disease is important since clinical assessments can only provide a brief and limited view of a patient's condition. However, traditional approaches rely heavily on patients' self-reports or diaries, which are subjective and often lack of necessary details. In this work, we instrument a handle that can be attached to cutlery with inertial sensors to collect motion data unobtrusively. By analyzing the data of patients and normal people collected in the clinic, we demonstrated that our machine learning based model can not only distinguish between patients and normal people, but also identify the disease levels in a fine-grained manner. To further understand how the self-tracking data is used in clinic, we conducted a semi-structured interview with several clinicians. Through the interpretation from the perspective of both physicians and patients, we found that our handle can help the physicians better understand disease progression and promote patients' engagement in tackling the disease.

**Keywords** Parkinson's disease (PD) · Self-tracking · Daily monitoring · Inertia sensor

## 1 Introduction

Parkinson's disease (PD) is the second-most common neurodegenerative disorder which is accompanied by a wide variety of motor [e.g. tremor, bradykinesia, rigidity, and impaired postural balance (Patel et al. 2009)] and non-motor

symptoms [e.g. hyposmia, sleep disorders, depression and constipation (Schapira et al. 2017)]. Based on United States Census Bureau projections, it is estimated that the frequency of PD will increase fourfold by the year 2040, making it an even larger burden on patients, their families and the whole society (Obeso et al. 2000). Levodopa is the most effective medication for PD treatment and almost all patients require levodopa therapy during the course of the disease (Jankovic 2008). However, the use of high-dose levodopa in early stage of treatment can result in the emergence of motor complications such as motor fluctuations (Obeso et al. 2000). It seriously limits the patient's mobility, and there are approximately 40% of the PD patients experience motor fluctuations by 4–6 years of treatment (Kikuchi 2007). Worse still, people with PD are commonly assessed every 6 months (Vega et al. 2018), which makes it difficult for clinicians to take control of the disease progression and response to emergencies timely. Thus unobtrusive and long-term monitoring of PD in daily life is likely to contribute to the patient's treatment process.

Typically, traditional clinical scales such as the Unified Parkinson's Disease Rating Scale (UPDRS) (Goetz et al. 2008) and Hoehn–Yahr Scale (Hoehn and Yahr 1998) can be used to distinguish the severity and impact of the PD symptoms. The assessment of long-term medication response in

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clinical environment usually take the form of self-report (Patel et al. 2009, 2010) and patient diaries (Reimer et al. 2004; Marinus et al. 2002; Hauser et al. 2000, 2004; Lyons and Pahwa 2007; Vega et al. 2018). In the form of self-report, information about motor fluctuations is obtained by asking patients to recall the number of hours of ON (i.e., where medications effectively attenuate tremor) and OFF time (i.e., when medications are not effective) (Patel et al. 2009). The process is time consuming and the results are subject to the perceptual bias and recall bias of patients. The use of patient diaries requires patients to record their motor status on the paper or electronic device in daily life as the symptoms occur. Although it can improve the reliability, subjective bias still exists especially in those PD patients who are cognitively impaired (Goetz et al. 1997) and many features captured are useless for clinical decision making (Group 2001).

Recent advances in sensor and wireless technologies, signal processing methods, and pattern recognition algorithms have resulted in quantitative assessments of motor fluctuations (Bonato et al. 2004). Wearable sensors utilizing gyroscopes and accelerometers are the most commonly used (Patel et al. 2009; Salarian et al. 2007a, b; Bonato et al. 2004; Moore et al. 2007; Saito et al. 2004) as they can collect the data from daily activity of patients. However, wearing these devices for a long time can bring discomfort to the patient, and patients must have good compliance with the wearable devices. In addition, after collecting the daily motor fluctuations data of patients, most of the existing research only uses machine learning methods (Patel et al. 2009) or simple functions (Salarian et al. 2007b) to establish a mapping relationship with the traditional clinical scales, few studies on how the final analysis results are interpreted by both the clinician and patient. One cannot simply fold self-tracking data into established clinical practices without some work on the part of both the patient and the clinician (Mentis et al. 2017).

Our work explores the feasibility to monitor motor symptoms in PD via instrumenting daily artifacts with dedicated sensors. Specifically, we designed a handle with the inertia sensor and it can be attached to daily cutlery such as spoon and fork to collect the patient's motion data during meals. Compared to the wearable devices, the way of interacting is less obtrusive and the need for user compliance can be lower. Patients don't have any extra burden and the motion data is collected while they are eating. An evaluation study was conducted to validate that our device were able to distinguish between the patients and normal people, as well as identifying the disease levels in a fine-grained manner. Two types of motion features including tremor and bradykinesia were extracted and machine learning algorithms were used. By comparing different classifier, we found that using SVM classifier worked best with an average accuracy rate of 92%

and the Pearson correlation coefficient of the fine-grained regression by using random forest regression algorithm is 0.97. In order to understand whether our device can really help the clinicians and patients and how the analysis results are interpreted by them, we further conducted a semi-structured interview with several clinicians at a local hospital. Then we found that the clinicians are eager to learn about the abnormality of the patient's motor fluctuations. By presenting the visual charts of participating patients' tremor characteristics over 1 week, we also found our device can better help the clinicians guide the patient to adjust the dose of drugs. And patient's engagement will be improved if they receive a positive feedback. More interesting is that we found that patients may have mental illness if their complaint is not the same as the actual measurement value.

Thus, our contributions in this paper are two folds: first, we explored to monitor the motor symptoms in PD via daily artifacts. We designed a handle with an inertia sensors, which can be attached to the daily cutlery to collect the patient's motion data unobtrusively during meals. We proved that the data from patient's meal can be used for quantitative assessment of motor fluctuations. Second, we showed the interpretation of the daily self-tracking data from the perspective of both clinicians and patients. We found that our device can help clinicians gain understanding about patients' fine-grained condition and can promote patients' engagement in tackling the disease.

## 2 Related work

### 2.1 Task-based assessment of PD

Traditional diagnosis for PD depends mainly on the medical history and neurological examination by a physician (Jankovic 2008). A number of rating scales were proposed to distinguish the severity and impact of the PD symptoms. Hoehn and Yahr scale (Hoehn and Yahr 1998) is commonly used to compare groups of patients and to provide gross assessment of disease progression, ranging from stage 0 (no signs of disease) to stage 5 (wheelchair bound or bedridden unless assisted) (Jankovic 2008). Then stages 1.5 and 2.5 were later added to help describe the intermediate course of the disease. The Unified Parkinson's Disease Rating scale (UPDRS) (Goetz et al. 2008) is the most well established scale for assessing disability and impairment (Ebersbach et al. 2006). Since motor impairment is the most dominant symptom of PD, which include *tremor*, *bradykinesia* (i.e., slowness of movement), *rigidity* (i.e., resistance to externally imposed movements), and *impaired postural balance* (Patel et al. 2009), patients were usually asked to complete specified actions to diagnosis or assess the severity of the disease. For example, the finger-tapping (FT) test requires

the subjects to repetitively tap the pad of the index finger against the pad of the thumb (Agostino et al. 1998), which is more difficult for the Parkinson's patients. In the gait study conducted by Schaafsma et al. (2003), subjects were instructed to stand up from a chair, walk at their normal pace on level ground for 20 m, turn and walk the same route back, ending with a half turn and return to a seated position. Patients with PD have higher variability of stride and the risk of falling. Voice-related tests have also been used for PD assessment, Fox and Ramig (1997) instructed the subjects to take a deep breath and say "ah" for as long as they can. Results revealed that subjects with PD were lower in vocal SPL (2.0–4.0 dB SPL; 30 cm). In the clinician-scored motor section of UPDRS (UPDRS Part III) (Goetz et al. 2008), there are more task-based motor impairment assessment such as hands opening and closing (items 24), heel tapping (items 26), and arising from chair (items 27). However, task-based assessment of PD only works when patients come to the hospital for outpatient visits, and relies on experience of the clinician to make a diagnosis. The patient cannot self-assess at home, and it is not conducive to long-term monitor the disease progression in daily life.

## 2.2 Daily monitoring of PD

Daily monitoring of PD has received much attention recently (Mcneaney et al. 2014, 2015; Krause et al. 2013; Salivia and Hourcade 2011), both subjective and quantitative methods for daily motor symptoms assessment have been widely explored. In clinical practice, one of the common used methods is self-report (Patel et al. 2009, 2010). Information about motor fluctuations is obtained by asking patients to recall the number of hours of ON (i.e., where medications effectively attenuate tremor) and OFF time (i.e., when medications are not effective). However, patients often have difficulty distinguishing the symptoms, which results in perceptual bias and recall bias (Patel et al. 2009). And the information is not always representative since the clinical environment is unfamiliar and sometimes rather stressful to the patient (Zwartjes et al. 2010). Another approach is the use of patient diaries (Reimer et al. 2004; Marinus et al. 2002; Hauser et al. 2000, 2004; Lyons and Pahwa 2007; Vega et al. 2018; Nyholm et al. 2004), which allow patients to stay in their home environment. Patients are required to log their motor status choosing among 3, 4, or 5 different states, every 30 min for 2–7 days (Hauser et al. 2004; Reimer et al. 2004). Whereas the traditional paper diaries may not reflect reality because of a lack in compliance or retrospective data entries, electronic diaries were used in Lyons and Pahwa (2007) and Nyholm et al. (2004). Recently, Vega et al. (2018) went back to analogue and found out that pen and paper are a suitable method to collect longitudinal day-to-day fluctuations. Although the patient diaries can record

in time when the patient's symptoms occur, many features captured are useless for clinical decision making (Group 2001), and the results can be troublesome (Golbe and Pae 1988; Brown et al. 1989). For example, Goetz et al. (1997) tested the efficiency of a patient-training videotape on motor fluctuations for on-off diaries, they found the ratings by 12 of 32 PD patients differed by more than 80% from those of a trained observer.

The need for quantitatively monitoring the motor symptoms in daily life has resulted in growing interest in sensor technology. Inertial sensors including accelerometer and gyroscope (Patel et al. 2009; Salarian et al. 2007b; Ghika et al. 1993; Moore et al. 2007; Saito et al. 2004; Spieker et al. 1995; Mazilu et al. 2014) are the most common used due to their portability and wearability. Ghika et al. (1993) and Spieker et al. (1995) were among the first investigators to explore the use of accelerometers and other sensing technology to monitor patients over extended periods of time. Recent advances in sensor features, wireless communication, signal processing, and pattern recognition have resulted in quantitative assessments of motor fluctuations (Bonato et al. 2004). Moore et al. (2007) explored to mount inertial sensor around the shank (just above the ankle) and analysis the variable stride length for long-term monitoring of gait in PD. Saito et al. (2004) quantitatively evaluated motor activity through Lifecorder, which contains an acceleration sensor and can be attached to the waist belt. They found that data obtained with the device correlated well with the UPDRS and Hoehn–Yahr grading. Gyroscopes were used by Salarian et al. in study (Salarian et al. 2007b), they proposed an algorithm to quantify the tremor and bradykinesia through the gyroscopes fixed to each of the forearms. They also found the tremor amplitude showed a high correlation to the UPDRS tremor subscore, which can be described leveraging a logarithmic function. Patel et al. (2009) worked on developing a wearable system that positioned on both upper and lower limbs. In their study, SVM classifier was used to estimate the severity of symptoms and motor complications.

However, wearing these wearable sensors for a long time will bring discomfort to the patients and require high user compliance. Besides, we still have little understanding of what kind of help does these systems bring to clinicians and how to contribute to patients' treatment.

## 2.3 Self-tracking data in clinic

Self-tracking can help chronic illness patients take more control over their health, but the participation of doctors is important for interpreting tracked data accurately (Cook 2014). Within CSCW and HCI, researchers have regularly addressed the need for clear and frequent communication and engagement between patients and clinicians (Coovert et al. 2012; Liu et al. 2011). The existing work that is most

closely related to our work is Mentis et al. (2015), which presented evidence that assessing a patient's motor function, the level of disability, and the efficacy of treatments are iterative and constructive acts reliant on an alignment of shared perceptions between clinician, patient, and lay caregiver—that which they termed co-interpretation. In their follow-up work (Mentis et al. 2016), they further showed the changes that occur in clinical co-interpretive practice by the use of a simple movement sensing system in clinical practice. For example, the patient's felt experience can be validated by the sensor and clinicians can use the data as prompts for patients to further reflect and share their perceptions. However, their research is still in the outpatient setting, patient's movements can be directly observed by the clinicians, which will have a preconceived effect on the data interpretation. A more recent study conducted by Mentis et al. (2017) explored how the presentation and shaping of self-tracking data is enacted via talk and actions. The data was collected from a Fitbit Zip activity tracker worn by the patients of PD for 4 weeks. Compared to their work, the data used in our research is directly related to the disease characteristics, which is closer to the patient's condition. Besides, we also extracted multidimensional features from the raw motion data and mined more information for the clinicians.

### 3 Design

Inspired by the previous work, we finally decided to combine the Inertial Measurement Unit (IMU) with the artifacts commonly used in our daily life instead of wearable devices to monitor the motor fluctuation. While these household items are used, the sensor records user's motion information unobtrusively and assess their motor function quantitatively. But what kind of daily necessities should we choose is an import issue. Considering that our equipment is used by the elderly in their daily lives, the following design guidelines must be followed.

- *Availability* Enabled to reflect motor symptoms, its actions can basically correspond to the clinical examination scale.
- *Necessity* Used commonly in daily life even multiple times per day, for real-time monitoring the motor fluctuation.
- *Universality* User actions should not be too complicated for elderly, best to meet various cultures including East and West.

Based on the above design guidelines, we initially chose the spoon as the carrier for sensor implantation. Firstly, by holding discussions with clinicians at a local hospital,

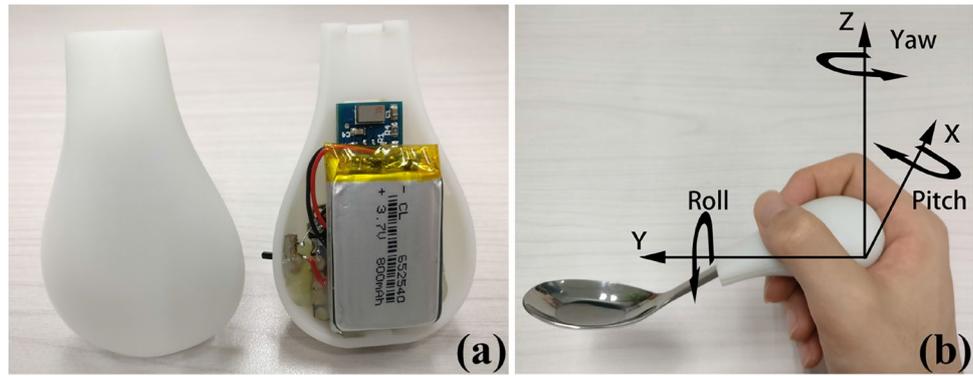
users have the functions of grasping, gripping, pinching, and moving in accordance with the provisions of the clinical medical scale when using a spoon. Secondly, spoons are very common used in daily life, especially for elderly to use spoons for three meals a day. This is related to the time they take the medicine (i.e., dopaminergic medications), which helps to better observe the efficacy of drugs. Finally, spoons are accepted globally not limited to Chinese and using actions is also very simple.

The design was implemented as an initial prototype by attaching an IMU and a battery on the handle of the spoon. The IMU module contains a tri-axis accelerometer (MMA7455L by Freescale Semiconductor, range:  $\pm 16$  g, sensitivity:  $6.1e-5$ g) measuring the accelerated velocity in three-dimensional space and a tri-axis gyroscope (ITG-3200 by InvenSense, range:  $\pm 2000^\circ$ /s, sensitivity:  $7.6e-3^\circ$ /s) measuring the angular velocity of hands movement in roll, yaw and pitch direction. The weight of IMU module is 4g and dimensions are  $15.24 \times 15.24 \times 2$  mm (W  $\times$  H  $\times$  D). All data is recorded with a sampling rate of 40 Hz, which can detect movements of up to 20 Hz according to the Nyquist Theorem. The data is transmitted to a laptop via Bluetooth (RN-41) at 9600 Bd. The battery we used is a 3.7-V 800 mAh lithium polymer battery.

We presented our initial spoon prototype to clinicians and patients at the hospital, which underwent three distinct iterations to refine its appearance and technical infrastructures. The first iteration was pilot tested by three clinicians and two ward nurses, they suggested that we should add a shell to the spoon handle to avoid the safety hazard that patients may spill the soup on the sensor. Then we made a handle shell that fit people's grips through 3D printing technology, and ensured that the sensor is well sealed except a gap for Bluetooth communication. After refining, later iterations were given to five patients for feedback, they were concerned about the cleaning and replacement of the spoon. Consider this issue and to make our device more versatile, we attached the sensor directly to the handle of the shell, which separates the sensor from the spoon. That makes it easy to remove the spoon for cleaning or replacement, and the handle with sensor can be used on other cutlery such as forks. The patient's family also suggested us to add a battery charging interface and an on/off switch to control the device, both of which were presented in our final prototype.

Figure 1 shows the final prototype and we attached it on a spoon. The IMU sensor and battery used in the device are the same as in our initial prototype. The acceleration sensor reflects the speed of the movement of the user in the three-dimensional space (x, y, z-axis) during the use of the spoon; the gyroscope sensor reflects the deflection rate of the three-axis tilt (Roll, Yaw, Pitch) change speed.

**Fig. 1** The 3D printed handle attached on the spoon (a) and the coordinate system established on the handle (b)



**Table 1** Summary of the demographic and clinical information of the study cohort (25 subjects)

n (total n = 25)	PDs	CNTs	Significance
	13	12	n/a
<b>Demographics</b>			
Women (%)	7 (53.85%)	5 (41.67%)	n/a
Men (%)	6 (46.15%)	7 (58.33%)	n/a
Age #avg (std)	57.46 (12.77)	56.08 (7.85)	n.s. (p = 0.35)
Education #avg (std)	10.77 (3.35)	11 (3.46)	n.s. (p = 0.85)
<b>Clinical characteristics</b>			
UPDRS part III #avg (std)	7.15 (3.48)	0.0 (0.0)	sig. (p < 0.001)
Hoehn and Yahr #avg (std)	1.77 (0.93)	n/a	n/a

With the exception of clinical characteristics (UPDRS-III score), the two groups are reasonable matched in terms of demographics as no significant difference was observed (two-side Mann–Whitney U test) *n/a* not applicable, *sig.* significant, *n.s.* non-significant

## 4 Evaluation

Our first study explored the feasibility of using our device for PD assessment by analyzing data from patients and normal people collected at the outpatient clinic of a local hospital. We extracted physically meaningful features, not only distinguished between patients and normal people through the classification algorithms, but also identified the disease levels in a fine-grained manner through regression algorithms.

### 4.1 Patient and procedure

We collected 25 subjects data from hospital clinic composed of 13 people diagnosed with PD and 12 healthy controls. All of them are right-handed. Table 1 summarizes the demographic and clinical information of these subjects. During the consultation time, a clinical evaluation



**Fig. 2** The subject drunk water with our spoon in clinic

including the Hoehn–Yahr scale and UPDRS-III test conducted by a disorder expert. After the clinical assessment, subjects were asked to drink a bowl of water (345 ml) using the spoon with our designed handle (Fig. 2). IMU data was collected at the same time and it took about a minute for each subject to drink the water. PD subjects were tested during their 'ON' state.

The study procedure was approved by a local hospital. All participants in the study gave informed consent prior to enrollment.

### 4.2 Data analysis

The original sensor data contains three-axis acceleration data three-axis gyroscope data. In order to enable the computer to accurately distinguish between patients and normal people, even to identify the disease levels in a fine-grained manner, we processed the original data and extract the relevant features of the PD. Finally, the machine learning classifier and regression methods were used to obtain the ideal results.

### 4.2.1 Signal filter and integration

We analyzed the data from the two characteristics of PD: tremor and bradykinesia. Thus two infinite impulse response (IIR) filters based on an elliptic design were used. One of them is a high-pass filtered with a cutoff frequency of 1 Hz to remove the effect of gross changes in the orientation of body segments (Hoff et al. 2001), and the other is a low-pass filtered with a cutoff frequency of 3 Hz to remove the effect of tremor for the analysis of bradykinesia (Patel et al. 2009).

In order to integrate the axis data and reduce the dimension, two one-dimensional “signals” are computed from the raw accelerometer and gyroscope axes.

- *MAG* The magnitude (Euclidean norm) of the signal around the x-, y-, and z-axes. This is to minimize errors resulting from slight variations in the orientation of sensors (Espay et al. 2011).
- *PC* The projection of the three-dimensional accelerometer signal onto its first principal component. This is the movement along the axis that demonstrates the most variance within this window (Morris et al. 2014).

### 4.2.2 Sliding window

It has been proved that the error values appear to plateau with a window of 5 s or longer for tremors, but a longer window is needed for bradykinesia because it is marked by lower frequency components than tremor (Hoff et al. 2001). Thus we windowed the data into 6-s windows sliding at 5 s (i.e., each window shares 1 s of data with previous window).

### 4.2.3 Feature extraction

Our feature set aims to capture the symptom of PD including tremor and bradykinesia. Tremor in PD is generally characterized by a frequency of approximately 4–7 Hz for rest and 6–13 Hz for postural/kinetic (Bhavana et al. 2016), hence we anticipate to distinguish tremor based on the frequency characteristics of the signal (e.g. the dominant frequency, median frequency, and power distribution). Approximate entropy is used to quantifies the degree of irregularity and the unpredictability of fluctuations in time series data (Abhinaya and Thanaraj 2016), the more complex the time series, the larger the approximate entropy. We anticipate the Parkinson’s patients to have higher irregularities due to tremor. On the other hand, the normal subjects commonly move with higher accelerations and energy than bradykinetic subjects (Griffiths et al. 2012), thus the peak value and mean spectral power were calculated as part of the bradykinesia features. Moreover, we calculated the speed by integrating the accelerometer and gyroscope data via the trapezoidal method with unit spacing. The range and the root mean square of the speed were used as the remaining bradykinesia features. Table 2 shows the features explored in this study. Each 6-s window is transformed into eight features. Note that there are four signals, thus in total we have 32 dimensions in the feature vector.

### 4.2.4 Classification

Every 6-s window in our training data was labeled “healthy” or “unhealthy” from the ground truth information of the participants given by the specialist. For each window, we computed these 32 features, and compared four classifiers including K-Nearest Neighbor (KNN), Adaboost, Random Forest and Support Vector Machine (SVM) with linear kernel. The

**Table 2** Features explored in the study

Feature name	Description
<b>Tremor features</b>	
Dominant frequency (DF)	The frequency at which the maximum power of spectrum occurs (Patel et al. 2009; Salarian et al. 2007b)
Median frequency (MF)	The point where the power is equally divided between the upper and lower parts of the spectrum (Perumal and Sankar 2016)
Power distribution (PD)	The amount of power distributed in the 4–13 Hz range around the total power in the spectrum (Perumal and Sankar 2016)
Approximated entropy (AE)	Approximate entropy estimates the effect of PD on the complexity of the tremor time series (Lukšys et al. 2018; Gil et al. 2010)
<b>Bradykinesia features</b>	
Peak (PK) mean spectral power (MSP)	The maximum amplitude of the signal and the mean of power spectral density between 0.2–4 Hz are calculated to reflect the motion energy (Griffiths et al. 2012)
Speed range (RG) speed root mean square (RMS)	The range and RMS are calculated to reflect the difference in speed (Dai and D’Angelo 2013; Kim et al. 2011; Dai et al. 2015)

probability of either “healthy” or “unhealthy” for each 6-s window is predicted and the final prediction of a participant depends on the normalized results of all the windows in his data. The machine learning models were built in Python using scikit-learn package. We are also very interested in the role of different sensors in classification, so based on the best classifier, we further analyze the classification results using only acceleration sensor or gyroscope sensor.

#### 4.2.5 Regression

In order to identify the PD levels in a fine-grained manner, we further established a random forest regression model (Ho 1995) to fit the data. The random forest regression learns shallower, more isolated trees instead, reducing the possibility of nonsensical interactions between features across tasks (Mariakakis et al. 2018). We still used the 6-s sliding window data, and the corresponding label of the data is the Hoehn–Yahr scale. However, there is a problem with sample imbalance in our data, especially fewer samples with high disease severity. So we oversampled the patient data so that the number of samples per disease level is almost the same. And to prevent overfitting, we used the SMOTE algorithm (Chawla et al. 2002) instead of simple copy of the sample for oversampling. The idea of SMOTE algorithm is to use the similarity of niche samples in special spaces to generate new samples. The total number of final samples is 72, with an average of about ten samples per level.

### 4.3 Results

#### 4.3.1 Feature analysis

This study mainly adopted two types of features including tremor features and bradykinesia features. To illustrate the identifying ability of our features and provide some preliminary insight into the statistical properties, we used one-way analysis of variance (ANOVA) test to determine if there are any significant differences between the mean values of the two groups (PD and healthy controls), and plotted the box diagram, which show the likely range of variation (the interquartile range or IQR) of a distribution. The green box represents the Parkinson's patients and the yellow box represents the healthy control group. Results indicate that these features can provide powerful identifying capability.

For tremor features, it can be seen from Fig. 3 that the patients' frequency value, high frequency ratio and irregularity are generally higher than normal people. Among these features, the number of signals with significant difference in the AE feature was the most, all signals showed significant differences ( $F_{1,23} = 20.105$ ,  $F_{1,23} = 17.6$ ,  $F_{1,23} = 27.267$ ,  $F_{1,23} = 20.154$ ,  $p < 0.001$ ). But for DF feature,

only two signals have the significant differences ( $F_{1,23} = 8.245$ ,  $p = 0.009$ ;  $F_{1,23} = 4.497$ ,  $p = 0.045$ ). This may be because in our study, we analyzed the frequency when a patient was drinking water, the maximum energy will appear in the low frequency part at many times. Note that the domain frequency of patients and normal people is concentrated below 4 Hz, which happens to be the frequency range of voluntary activities (Perumal and Sankar 2016), the distinction in DF feature is not obvious enough. And the MF feature is better than DF feature because it reflects the overall center of the energy distribution. We also found that features performed on the PC signal are better overall than MAG because all the four features have significant differences among the data except for DF feature on GYRO\_PC ( $F_{1,23} = 3.672$ ,  $p = 0.068$ ). This may be because the action of smashing with a spoon itself will bring about dramatic changes, the MAG signal integrates three directions by simply squared and superimposed will contain a lot of noise interface, while the PC signal can reflect the more representative information of the three signals.

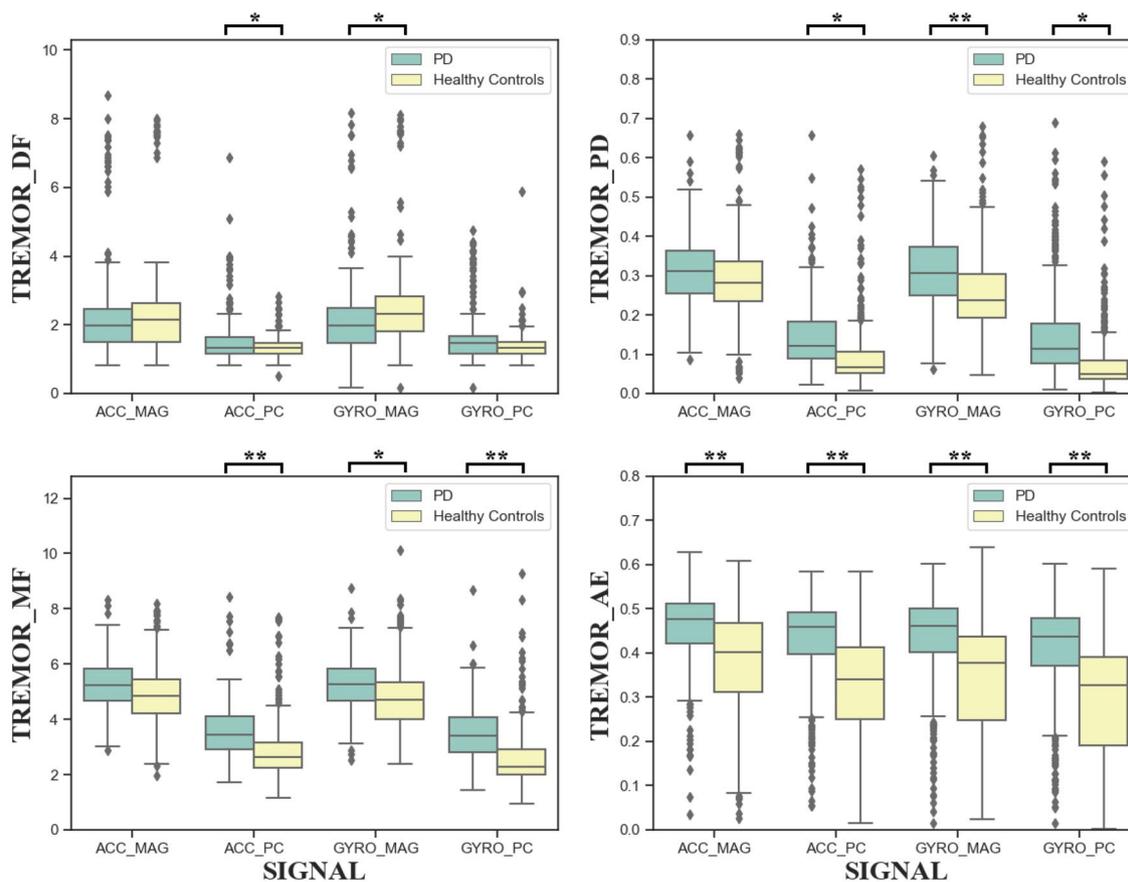
For bradykinesia features, to plot signals of different magnitudes together, we used the min–max normalization methods. The formula is given as:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}. \quad (1)$$

Then according to Fig. 4, the moving speed and energy values of the PD patients are generally lower than normal due to bradykinesia. Among the features, significant differences exist except for the RG feature and the RMS feature of ACC signals ( $F_{1,23} = 1.446$ ,  $p = 0.241$ ;  $F_{1,23} = 2.847$ ,  $p = 0.104$ ;  $F_{1,23} = 1.716$ ,  $p = 0.203$ ;  $F_{1,23} = 2.847$ ,  $p = 0.105$ ).

#### 4.3.2 Classification results

Our preference for that approach was guided by its good performance relative to a total of five machine learning algorithms tested, and whose performance in terms of AUC, sensitivity (Sens), specificity (Spec), and accuracy (Acc) are shown in Table 3. The algorithms were tested with leave-one-out cross validation. Results showed that SVM was better than any of other classifiers, as it classified correctly 91.67% of the PD participants and 92.31% of the healthy participants, with AUC of 0.98 and accuracy of 92.0%. By comparing the two sensors, we found it was reasonable that the classification result of two sensors was better than that of single sensor. However, we also found the classification result of only using gyroscope sensor was better than acceleration sensor, which meant that the symptoms of Parkinson's patients were more pronounced in angular deflection.



**Fig. 3** Boxplot of tremor features. Statistically significant differences are noted as:  $p < 0.001(**)$  and  $p < 0.05(*)$

### 4.3.3 Regression results

The regression results are shown in Fig. 5, including the actual Hoehn–Yahr scales and predicted scores for 72 samples. The mean absolute error is 0.166 and the Pearson correlation coefficient between them is 0.97. Thus a fine-grained distinction can be made between diseases by using a random forest regression, which is the basis for our long-term monitoring of diseases.

## 5 Understanding the role of PD monitoring

In order to find out whether our device can really help the physicians and the elderly in practice, we conducted a semi-structured interview with several clinicians at the local hospital. As our motivation was to explicate the talk that come together with the self-tracking data, which is not achieved with one quote, but rather a series of talk. Thus we presented our findings as vignettes from the conversations, focusing on three main themes: clinical demands, the interpretation of the visual data, and the help for the patients. In the

following sessions, RS refers to our researchers, CN refers to the clinicians.

### 5.1 Vignette 1: clinical demands

At the beginning, we are concerned about the problems in the treatment and long-term monitoring of the PD among clinicians. Although a lot of related work has been investigated, we still want to know the real thoughts of the clinicians and the current situation, including the clinical diagnosis, how the patient adjusts the drug and what kind of help can our device provide for them.

*RS: How to ask the PD patient's condition in the clinic?*

*CN: For example, "Is the hand shaken so bad?", "Is it okay to walk?". The complaints of Parkinson's patients will generally be "I am shaking hands" and "I am walking slowly." Clinical examinations will also allow patients to write, draw spirals, and do some paper and pen movements. All of them depend on our subjective judgement.*

Therefore, in the clinical diagnosis of PD, the motor characteristics are a very important basis for judgement. The clinician will check the patient's athletic ability and make

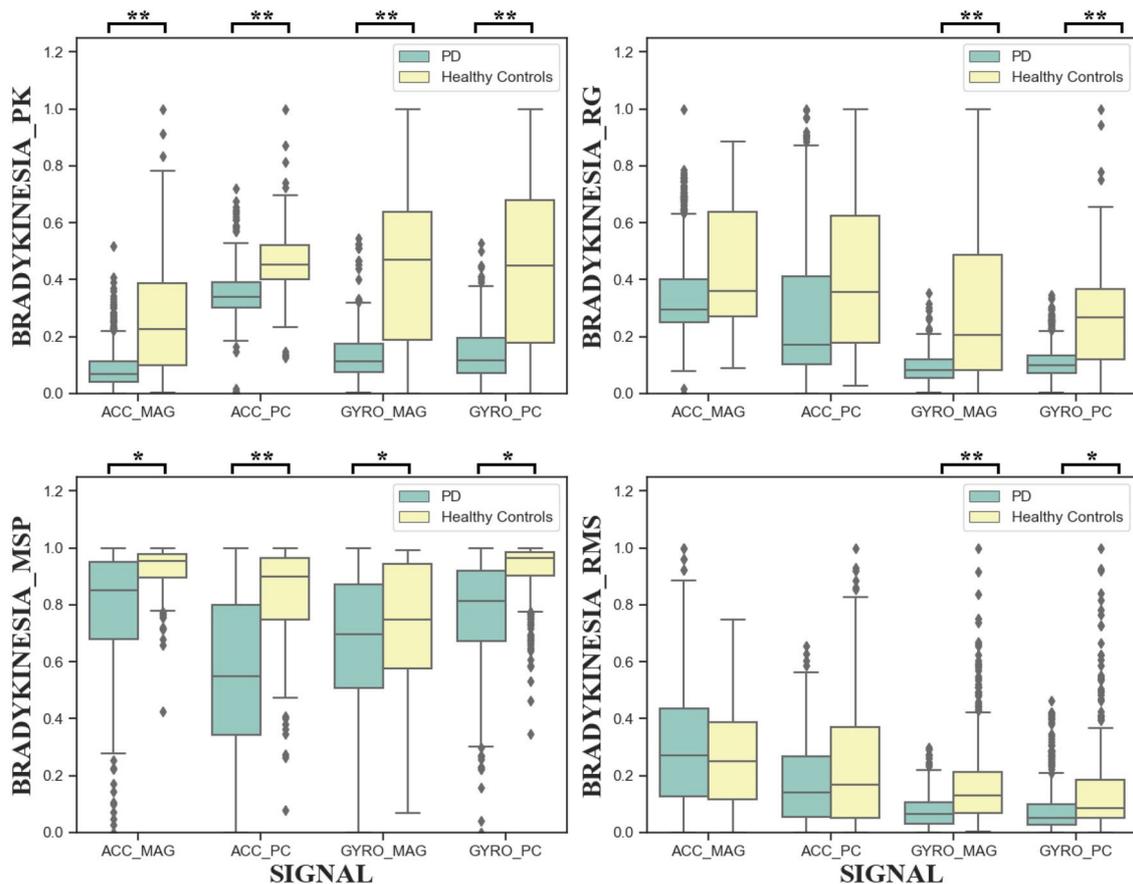


Fig. 4 Boxplot of bradykinesia features. Statistically significant differences are noted as:  $p < 0.001(**)$  and  $p < 0.05(*)$

Table 3 Classification performances of different algorithm

Algorithms	AUC [5% 95%]	Spec (%)	Sens (%)	Acc (%)
KNN	0.95 [0.78 0.99]	81.81	78.57	80.0
Adaboost	0.95 [0.76 0.99]	90.0	80.0	84.0
Random forest	0.95 [0.81 0.99]	83.3	84.6	88.0
SVM	<b>0.98</b> [0.92 0.99]	<b>91.67</b>	<b>92.31</b>	<b>92.0</b>
GYRO+ + SVM	0.95 [0.78 0.99]	90.0	80.0	84.0
GYRO + SVM	0.95 [0.79 0.99]	90.9	85.71	88.0

The best performing algorithm is bold

subjective evaluations based on their experience. We also noticed that most patients usually wait until the symptoms are serious before they come to the hospital for examination. Some early illnesses are very insidious and have a low incidence, so identifying such mildly ill people in advance is very meaningful for the diagnosis of existing PD.

RS: After the diagnosis of Parkinson's patients, how often do they review and do you want to know the daily status of the patient at home during the period before the review?

CN: They will be given medication after diagnosis and wait for one to three months before reviewing. When they

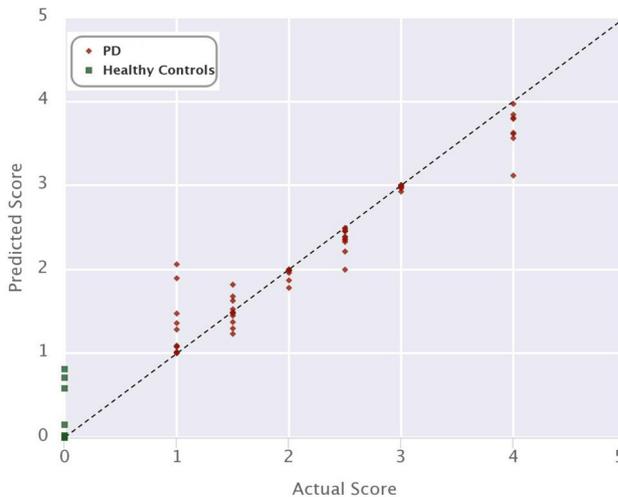


Fig. 5 Regression results of Hoehn-Yahr scale

come to review, we especially want to know the reaction of PD at home, which is related to how we adjust the dose of the drug for them. We lack an objective measure because

some patients may not express symptoms due to their age or unclearness and some patients don't even want to tell the truth. And the control effect of drug on mid-to-late Parkinson's patients is irregular, daily monitoring is necessary.

*RS: So how to adjust the drug dose? Are the patients adjusting the dose themselves? Is there a subjective factor?*

*CN: Adding slowly from the initial dose can control the symptoms, and it cannot be excessive, which can cause side effects. We will guide the patient how to adjust the medicine and avoid the patient's own adjusting. The dosage itself depends on the patient's subjective feelings.*

It can be seen that there is currently a great deal of uncertainty about the dose adjustment in the treatment of Parkinson's patients. Although in the early stage of PD, the clinicians can give guidance on the dose of Parkinson's patients based on experience and current symptoms, the efficacy of the drug will gradually weaken in the middle and late stages of the disease, and the patient will also have dyskinesia, which is very troublesome for the clinician's drug adjustment. Through our device, we can provide an objective evaluation value after each meal as a reference for clinicians and patients to adjust the dose.

*RS: What do you think our equipment can help you in other ways?*

*CN: When we look at the clinic, we only know the patient's performance at the current time point, which may be the time when the patients has taken the medicine. We may think that the current state is good but can't see the state of whole day. On the other hand, the Parkinson's patients need long-term management and the course of PD is about 5–10 years. Therefore, if you have a patient's electronic data database, it will facilitate future management and follow-up. And at present, we don't know when the course of PD will suddenly deteriorate and the natural course of the disease. If the disease course can be detected in the future, it will help to describe the course of the disease and Analysis the sudden influence factors.*

We found that a detailed report on the patient's condition is very necessary. Compared to the current diagnostic process, we store the detail motor fluctuations information of the users for each meal per day in the database, and provide an objective reference for clinician's judgments when patients review at the hospital. We can also contribute to long-term management of the disease. For example, when a patient with advanced PD comes back to the clinic, we can check the record of his illness ten years ago, which will help clinicians to fully understand the condition and adopt the best treatment plan.

## 5.2 Vignette 2: visual data interpretation

Visualization chart is the most intuitive way to present a patient's condition to a clinician. Here we presented a simple

visualization method based on the histogram. The abscissa indicates 7 days of a week, the ordinate indicates the median frequency features of the patient, and the three columns correspond to three meals a day. Before collecting data from real home environments, we simulated several possible situations of patients according to the description of clinicians. We want to know what kind of interpretations will be made when clinicians see these forms, and how this will help them better diagnose the condition of Parkinson's patients.

*RS: If the patient's self-tracking tremor frequency data within one week is shown below, what does it mean and what will you do ?*

*CN: From Fig. 6a, the patient's fluctuations are relatively stable, so it is enough to maintain the dose of the original drug.*

*CN: From Fig. 6b, the patient's condition is deteriorating, and the drug control is not good. We will consider increasing the dose of the drug. We will also check if he has other symptoms.*

*CN: Fig. 6c reflects the difference between the motor fluctuation of the patient between morning and other times, so we will consider increasing the dose of the morning drug.*

*CN: From Fig. 6d, in the middle two days, the patient's fluctuations were abnormal, but then returned to normal. This may be because the patient has forgotten to take the medicine for two days or has been affected by the external environment.*

Through the above analysis, we found that various situations occur in the daily life of the patient. However, the clinicians are not well aware of these situations at present, and it is difficult to make a comprehensive judgment through the patient's subjective appeals, especially for the control of doses. However, according to the information provided by our results, this missing information can be compensated.

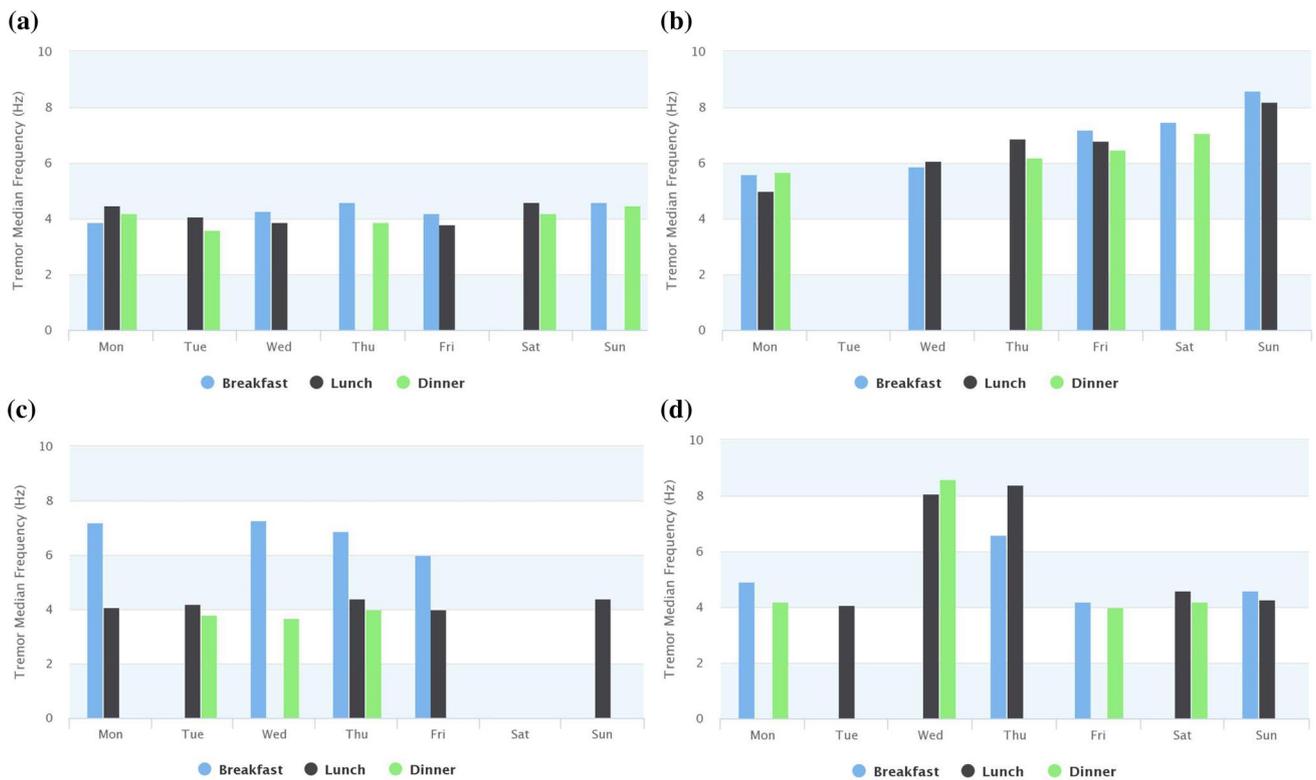
## 5.3 Vignette 3: help for patients

It is also a problem we want to know that how can our device help the patients after they use is. Not only is it limited to adjusting the dose based on objective data every day, we also explored whether positive feedback on the mental level would help to improve the condition, and finally there are some interesting findings.

*RS: From the patient's point of view, can our data help?*

*CN: In the clinic, patients will have more severe symptoms due to psychological stress, but using our equipment can provide real data that they usually measure at home and participate in the treatment process. Besides, if the patients observes their data is normal every day, there will be a placebo effect. Positive psychological implications for the patients are like watching the sphygmomanometer measuring normal blood pressure or the pedometer walking a lot of steps every day.*

*RS: If the information the patient sees is negative and finds that his condition is worsening, will it increase negative feedback?*



**Fig. 6** Visualization of simulated patient data

*CN: The patients themselves can feel their own situation. Even without our data, the condition will worsen if it worsens.*

*RS: Is there a bias in the self-perception of Parkinson's patients, such as feeling aggravated but not actually aggravating?*

*CN: Some Parkinson's patients also have some mental emotional problems such as depression, so their subjective feelings will be different from healthy people.*

At the first time of consultation, it is necessary to record the initial state of the patient as a baseline, so that the bias between the subjective feelings and real situations can be found. In addition, if the patient's subjective description is inconsistent with the clinician's view (symptoms and complaints are inconsistent), it may indicate that the patient has mental problems, and they may be recommended to refer to the psychology department for early diagnosis of mental illness. After they have improved their emotional problems, they can come back to do our checks and see if they are getting better.

## 6 Discussion

Our motivation of the study is to monitor the motor symptom of PD through the daily artifacts. Following the three design principles of availability, necessity and universality,

we designed a handle with inertial sensors and it can be attached to the daily cutlery. To ensure the validity of our device for daily monitoring, we first conducted an evaluation study and found that our device can not only distinguish the patients and normal people well, but also identify the disease levels in a fine-grained manner. In our research, we are also interested in how the self-tracking data is interpreted by clinicians and patients, and what kind of help can these data provide to them. Therefore, we conducted a semi-structured interview with several clinicians at a local hospital. In Vignette 1 and 2, we see that information about the patient's daily motor symptoms is really important to the clinicians. The weekly or even daily motor fluctuations of the patients are unstable, thus continuously control of drugs is necessary. One of the main aids of our device is to instruct patients to tailor medication to the fluctuations of their condition. And it also contributes to assist clinicians to master the trend of the disease. We see that patient's engagement can be improved through self-tracking results and a positive feedback will increase their confidence in Vignette 3. Another finding is that patients may have mental problem if the results are inconsistent with their feelings. Thus more information can be mined through clinical interpretation of the patient's self-tracking data. A more interesting thing is that during our

study, many patients reported that using the spoon with our handle is more comfortable than a normal spoon.

We hope that the interpretation given by the clinicians in our study can inspire the researchers who work in the related fields. However, there are some limitations in our research that should be considered. The number of patients explored in our study is not large enough and we just did an initial deployment. In the future, we want to make a complete system and look for large-scale Parkinson's patients for long-term follow-up experiments. And we believe that there will be more interesting discoveries in such an environment.

## 7 Conclusions

In this work, we explored to combine the IMU sensors with the daily artifacts to monitor the motor fluctuations of PD. After the iterative development, we finally designed a handle with inertia sensor that can be attached to the cutlery and unobtrusively collect motion data while eating. Through 25 subjects study for classification and regression, we can distinguish between patients and normal people with AUC of 0.98 and Pearson correlation coefficient of 0.97. A semi-structured interview validated that the self-tracking data can help clinicians better understand disease progression and can encourage patients' engagement for treatment.

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