Home-based Self-assessments and Early Risk Analytics for Parkinson's Disease

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Abstract

Parkinson's disease (PD) is the second most common neurodegenerative disorder that threatens the living quality of the older adults. Though there is no known cure for PD currently, identification of the disease in its earlier stages is crucial for delivering effective treatments, providing symptomatic benefits and sustaining patients to live in a healthier state longer. Besides, the daily condition of a patient needs to be monitored in an objective and convenient way, since the doses for PD medication may need to be adjusted over time based on the patient's response to the medication.

To achieve early identification and frequent monitoring of PD, we proposed a home-based self-assessment and early risk analytics platform for Parkinson's Disease. Using sensors embedded in the smartphones, the platform collects patient's testing behaviors for 9 mini-tests, each of which detects a representative symptom of PD. The data collected is in a standardized format, and hence can be

used conveniently for generating analytical insights, such as risk predictions and condition reports. Features characterizing the symptoms of PD are extracted from the patient's test behavioral data. A support-vector machine ensemble with bagging is applied to the extracted features to predict the risk of developing PD. The platform users only need to complete the mini-tests at home and the generated insights can be directed sent to users' smartphones or accessed online, helping the users to better understand their conditions and risk profiles.

Keyword: Parkinson's disease, home-based assessments, data analytics

I. Introduction

Parkinson's disease (PD) is a progressive nervous system disorder that is primarily characterized by motor symptoms[26]. In 2015, PD afflicted 6.2 million people and resulted in about 117,400 deaths globally [31, 32]. Evidence from studies suggests an increasing prevalence of PD with older age and its global prevalence increases from 1% among people aged 60 and above to 4% among people aged 80 and above [6]. In early stages, PD patients may suffer from shaking, rigidity, bradykinesia, difficulty with walking, and other motor symptoms [13]. As the disease progresses, PD patients may exhibit non-motor symptoms due to the degeneration of the nervous system, which may greatly deteriorate their quality of life [6, 13]. There is consistent evidence across studies that older adults with PD are more prone to depression and dementia [4, 13]. Besides, the PD patients may also experience problems with sleep, sensory and emotion [28], which greatly threatens their living quality.

Although there is no existing treatment that can stop or reverse the progression of Parkinson's disease [28], some treatments, such as the antiparkinson medication levodopa (L-DOPA), can help to alleviate the symptoms [33]. In early stages of PD, medications can help patients to control the symptoms and live a normal life longer. As the disease progresses and degeneration in nervous system accumulates, patients tend to become less responsive to medications [28]. Therefore, the identification of patients at risk and in earlier stages of the disease appears to be essential for devising any successful

neuroprotection, providing symptomatic benefits and sustaining patients to live normally longer. However, early and accurate diagnosis of the PD can be challenging because there are no biomarkers or neuroimaging or other clinical tests available currently to confirm the diagnosis. PD diagnosis is currently based on the presence or absence of various clinical features and the experience of the treating physician [19]. Due to the mildness of many early signs, patients may not undergo clinical examinations for PD during early stages and therefore, the best stage for treatment may have been missed when symptoms become noticeable. Besides, in order to help patients to sustain normal motor function over the day, the doses for PD medication may need to be adjusted over time based on the patients' response to the medication [1]. Therefore, continuous and frequent assessments are crucial for detecting possible PD signs early, evaluating the medication's effectiveness, and monitoring the disease progress.

Traditionally, the assessments and diagnosis of PD are performed by an expert, e.g., a movement disorder specialist, in a clinical setting. Typical procedures involve the evaluation of subject's overall condition according to standardized scales and questionnaires. Due to various cost and resource limitations, long-term and frequent monitoring of PD symptoms is impractical under the traditional approach. Home-based computerized tests provide new opportunities for self-administered assessments and remote monitoring of early PD signs, which can lead to timely diagnosis, early intervention, and consequent improvement of patients' quality of life. Without the need of a trained assessor and the presence of the subject at the clinic, the computerized mini-tests can be distributed over the Internet and self-administered. Compared to traditional scales and questionnaires which are often subjective as they rely on expert's judgments or subject's self-reports, computerized tests are more objective, more repeatable, and most importantly, more accessible. In this paper, we propose a self-assessment platform on smartphones to facilitate patients and caregivers to objectively screen PD symptoms and monitor the effectiveness of treatments in a home-based environment. This platform provides objective and convenient measurements to continuously capture the severity of PD symptoms and fluctuations, together with an effective and reliable way to analyze the testing result. There are 9 mini-tests in our platform. Each mini-test is designed in the light of a task for motor assessment in the Unified

Parkinson Disease Rating Scale (UPDRS) [10]. The users only need to complete the mini-tests at home rather than physically visiting the clinics and going through lengthy questionnaires. Using sensors embedded in the smartphones, the platform collects patient's testing behaviors. The data collected is standardized and can be used conveniently for generating analytical insights, such as risk predictions and condition reports, using machine leaning methods. Besides, generated insights can be directed sent to users' smartphones or accessed online, helping the users to better understand their conditions and risk profiles.

The rest of the paper is organized as follows. Section 2 reviews the relevant background on Parkinson's disease, its assessment and early detection, and existing computerized batteries. Section 3 presents the overall design concepts and each mini-test of mobile platform for PD assessment. Then, section 4 focuses on the feature extraction and data analytics. Section 5 describes the SVM ensembles with bagging used and presents the results of simulations conducted on the proposed platform. Using simulated patient data, the process from collecting data, analyzing data, to producing risk prediction is exemplified. Finally, section 6 concludes the paper.

II. Background

A. Parkinson's Disease

Parkinson's disease (PD) is a common geriatric disease, which may lead to a series of motion disorders such as hands shaking, rigidity, slowness of movement and walking [7, 17]. Many risk factors for PD have been identified, however, most of them have not been conclusively proven [6]. The most frequently studied relationships are an increased risk of PD with exposures to pesticides, and a reduced risk in smokers [3, 6]. There is also a potential linkage between PD and H. pylori infection that can prevent the absorption of some drugs including levodopa [5, 18]. The pathophysiology of Parkinson's disease is the death of dopaminergic neurons as a result of changes in biological activity in the brain with respect to PD [25]. There are several proposed mechanisms

for neuronal death; however, not all of them are well understood. Five proposed major mechanisms for neuronal death in Parkinson's Disease include protein aggregation in Lewy bodies, disruption of autophagy, changes in cell metabolism or mitochondrial function, neuroinflammation, and blood-brain barrier breakdown resulting in vascular leakiness [29]

B. Symptoms and Traditional PD Assessment

Symptoms of Parkinson's disease typically manifest in three aspects, motor, neuropsychiatric and other [13]. Four motor symptoms are considered cardinal in PD: tremor, slowness of movement (bradykinesia), rigidity, and postural instability[22]. Other recognized motor signs and symptoms include gait and posture disturbances such as festination (rapid shuffling steps and a forward-flexed posture when walking with no flexed arm swing). Freezing of gait (brief arrests when the feet seem to get stuck to the floor, especially on turning or changing direction), a slurred monotonous quiet voice, mask-like facial expression, and handwriting that gets smaller and smaller are also common signs [20]. The neuropsychiatric disturbances, which include disorders of cognition, mood, behavior, and thought, can range from mild to severe [4]. In addition to neuropsychiatric and motor symptoms, PD can impair other functions and lead to non-motor symptoms, such as sleep disorders, orthostatic hypotension (low blood pressure upon standing), oily skin, excessive sweating, urinary incontinence, and altered sexual function [13].

Currently, clinicians use Unified Parkinson Disease Rating Scale (UPDRS) [10] to gauge the course of Parkinson's Disease in patients. The UPDRS scale includes series of ratings for typical Parkinson's symptoms that cover all of the movement hindrances of Parkinson's disease. The UPDRS scale consists of the following five segments: 1) Mentation, Behavior, and Mood, 2) ADL, 3) Motor sections, 4) Modified Hoehn and Yahr Scale, and 5) Schwab and England ADL scale. Each answer to the scale is evaluated by a medical professional that specializes in Parkinson's disease during patient interviews.

Though exhaustive and highly agreed, UPDRS still has several flaws. Firstly, the testing results is subjective and corporal, especially for the Mentation, Behavior, and Mood part, due to

the fact that they are reported by patients and caregivers themselves. Secondly, the process of sitting through a test itself is intrusive for the patients, laying the burden to the test subjects mentally. Moreover, there are more than 40 questions in UPDRS, making the assessments very time consuming, highly labor and resource intensive, and hence, impractical in daily early diagnose and condition tracking.

C. *Technology-assisted PD Assessment*

Eyeing on the disadvantages of the traditional PD assessment approach, researchers have designed various more accessible tools to measure the severity of PD symptoms quantitatively and objectively. To this end, there are mainly three ways for detecting PD motor symptoms, aiming at electronic devices interaction, tremor and gait separately.

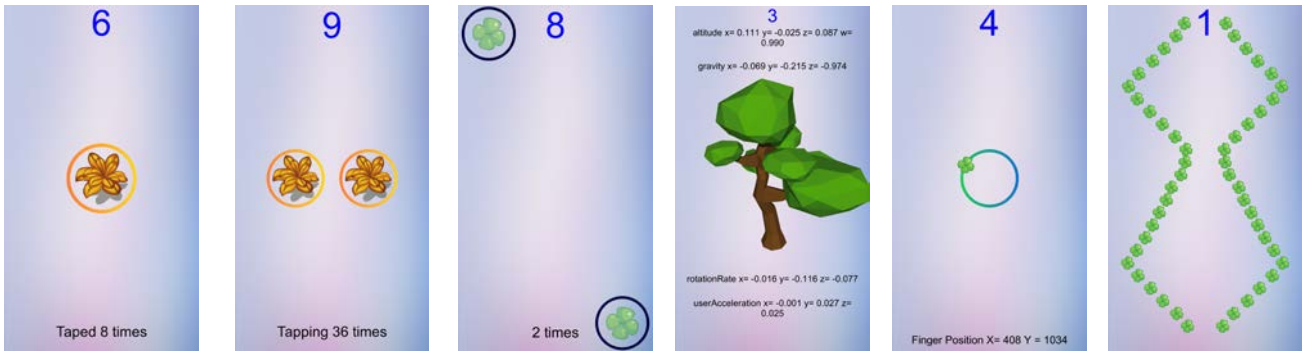
The research of typing pattern begins with daily interaction with a computer keyboard [9], which can be employed as means to observe and potentially quantify psychomotor impairment. With the development of mobile devices, the focus has shifted to touchscreen smartphones. Analysis of patterns emerging from finger interaction with touchscreen devices during natural typing [12] and computer vision (CV) method for quantification of tapping symptoms through motion analysis of index-fingers [15] are also applied to interaction with electronic devices.

Besides, tremor research is a vital part in PD diagnosis. At first, the focus is only on classifying the Parkinson disease's rest tremor between high or low frequencies [21], which shows the intensity of Parkinson's motor symptom. Then, it spreads to investigating the properties of oscillatory movement, at rest and in posture, in both the upper and lower limbs [24]. There is also research on analyzing tremor characteristics under resting-state and stress-state conditions, using an accelerometer on the finger [16], which focuses on normal people under two different states but contributes to PD tremor detecting. Moreover, an application named iSeismo uses the inbuilt accelerometer of the iPhone for rapid measurement of tremor frequency [14], closely matching the more sophisticated EMG analysis during tremor.

Isolated research on gait is also applied to PD diagnosis. Data captured from phones embedded accelerometer sensors can be used to recognize users based only on the characteristics of their walking gait [8, 27]. Instead of sensors embedded in mobile devices, independent accelerometers placed on the foot, ankle, shank or waist are also used to analyze gait features [2]. Besides, the continuous wavelet transform (CWT) is also employed to define an index for correctly identifying Freezing of gait (FOG) [23], which improves the accuracy of FOG detection significantly.

However, most of the existing works focused on one symptom only and ignore the correlations among symptoms, which may lead to incomplete evaluation outcomes for PD patients. To improve it, we propose an integrated home-based self-assessments and early risk analytics platform for Parkinson's Disease which turning the important part of the motion section in UPDRS into an easy-operating computerized system and with the features listed below:

- home-based and convenient for operation
- suitable for long-term self-assessments
- able to generate an effective early risk analytics result



(a) (b) (c) (d) (e) (f)

Figure 1: Screenshots of the mini-test in the PD assessment App: (a) single Finger Tapping, (b) alternate Finger Tapping, (c) tremor (rest, postural, kinetic), (d) micrographia, (e) Coordination, and (f) finger tapping (scissors)

III. **Mobile Platform for PD Assessment**

We designed 9 mini-tests to evaluate the PD risk of the test subject. By analysing the data collected from the test subjects using machine learning method, we can categorize the test subjects into different types.

A. Single Finger Tapping

As shown in Figure 1(a), there is one circle on the screen and the test subject is supposed to tap the screen within the range of the circle as fast as he can.

B. Alternative Tapping

As shown in Figure 1(b), there are two circles on the screen, the test subject should alternatively tap the screen at the position of the two circles as many times as he can.

C. Rest Tremor

In the Rest Tremor task, the test subject is supposed to sit still, rest the most affected hand on the leg of the same side, and hold the phone flat with the screen facing up on the palm of the hand. The test screen in shown in Figure 1(c), the appearance of which is the same for Rest Tremor, Postural Tremor, and Kinetic Tremor. The orientation of the tree on the screen changes to reflect the movement of the test subject's hand.

D. Postural Tremor

In the Postural Tremor part, the test subject should also sit still, but extend hand forward at shoulder height, and hold the phone with the screen facing up flat on the palm of the most affected hand.

E. Kinetic Tremor

In the Kinetic Tremor part, the test subject is required to sit still and hold the phone using the most affected hand. Then the subject starts from a position of outstretched arm extending sideways from the body at shoulder level, bends the arm at the elbow, brings his/her hand above head to heart in a semi-circle motion, and returns to original position using the same motion.

F. Micrographia

In this task, there is a circle on the screen in the first few seconds (see Figure 1(d)). The test subject should trace the circle with a finger of the most affected hand. The circle will disappear after a few seconds but the test subject is supposed to keep tracing the original circle for another short period.

G. Coordination

In this task, there is two symmetric trails on screen as in Figure 1(e), the test subject is supposed to trace the two trails from the bottom of the trails using the index finger from both hands simultaneously.

H. Finger Tapping

In this task, there are two circles on the upper left and bottom right corners (left-hand mode) or on the upper right and bottom left corners (right-hand mode) as in Figure 1(f), the test subject should place the index finger and thumb on the two circles, respectively, and then bring the index finger and thumb to the center of the screen to make the two fingers contact, repeat this action as fast as he/she can. Besides, there is a invisible circle on the screen. Only when the two fingers contact inside the circle, which means that they are close enough, can the tap counts valid.

IV. Feature Extraction

A. Single Finger Tapping

This test is used for detecting rigidity, early fatigue and bradykinesia. To achieve this goal, we extract several features of the data to analyze including: 1) total number of taps T_{t_s}; 2) number of valid taps T_{v_s}; 3) average tapping interval in the entire period I_{a_s}; 4) average tapping intervals in the first-half $I_{f_s}$and the second-half I_{s_s}.

According to UPDRS, the Single Finger Tapping task last for 10 seconds. During the time, we record every tap of the test subject, and calculate the distance between the tap and the center of the screen. If the distance is less than the radius of the circle we designed in the center, the tap is

noted as a valid one. By subtracting two time stamps of adjacent taps, we can get the tapping interval. The average tapping intervals in the first-half I_{f_s} and the second-half I_{s_s} is for detecting early fatigue since that Parkinson's patients are more likely to feel tired during the test than normal people, and hence, I_{s_s} is more likely to be bigger than I_{f_s}.

Mini-test	**Assessed PD Symptoms**	**Extracted Features**
Single Finger Tapping	Rigidity, early fatigue, bradyskinesia	Total number of taps T_{t_s}, number of valid taps T_{v_s}, average tapping interval in the entire period I_{a_s}, average tapping intervals in the first-half I_{f_s}, and the second-half I_{s_s}
Alternative Tapping	Rigidity, early fatigue, bradyskinesia	Number of valid alternative taps T_{v_a},total number of taps T_{t_a}, average tapping interval in the entire period I_{a_a}, average tapping intervals in the first-half I_{f_a} and the second-half I_{s_a}
Rest Tremor	Rest tremor	Tremor frequency f_r, average amplitude A_{avg_r}, maximum amplitude A_{max_r}, average standard deviation of quaternion
Postural Tremor	Postural tremor	Tremor frequency f_p, average amplitude A_{avg_p}, maximum amplitude A_{max_p}, average standard deviation of quaternion
Kinetic Tremor	Kinetic tremor	Kinetic tremor over the whole movement p_k, average amplitude A_{avg_k}, maximum amplitude A_{max_k}, average standard deviation of quaternion
Micrographia	Micrographia	Variation of tracking radius var_r, average drawing angular speed in the entire period ω_a, average drawing angular speed in the first-half ω_f and second-half ω_s
Coordination	Movement coordination	Total drawing time t_{t_c}, drawing length l_{t_c} and, drawing speed of the test subject v_{t_c}, sum of the left and right hands deviation d_{t_c}
Finger Tapping (scissor)	Rigidity, early fatigue, bradyskinesia, movement coordination	Total number of taps T_{t_f}, number of valid taps T_{v_f}, average finger moving speed v_{a_f} and distance d_{a_f} in the entire period, average finger moving speed v_{f_f}, v_{s_f} and distance d_{f_f}, d_{s_f} in the first-half and the second-half

B. Alternative Tapping

This task is for detecting finger coordination, rigidity, early fatigue and bradykinesia. Instead of collecting number of valid taps in task 1, we collect 1) number of valid alternative taps T_{v_a}, which only takes a matched left and right taps into account. Besides, we also take the following features

into account: 2) total number of taps T_{t_a}; 3) average tapping interval in the entire period I_{a_a}; 4) average tapping intervals in the first-half I_{f_a} and the second-half I_{s_a}.

We also record every tap of the test subject, but instead, we only consider a pair of matched left tap and right tap in the range of the circle as a valid tap T_{v_a}. For the other features as T_{t_a}, I_{a_a}, I_{f_a} and I_{s_a}, we take the same approach as Single Tapping.

C. *Rest Tremor*

There are motion sensors measuring acceleration forces such as tilts, shakes and swing. Accelerometer measures the raw acceleration, Gravity measures gravity only, and UserAcceleration measures only the acceleration applied by the user. The sensors use the physic relation

$$Accelerometer = Gravity + User\ Acceleration$$

The data captured by UserAcceleration is the main part for analysing.

Fast Fourier Transform (FFT) is used to deal with the UserAcceleration data. FFT is an algorithm that computes the discrete Fourier transform (DFT) of a sequence, or its inverse (IDFT). Fourier analysis converts a signal from its original domain (often time or space) to a representation in the frequency domain and vice versa [11]. Let $x_0, \ldots, x_{N-1}$ be complex numbers. The DFT is defined by the formula

$$X_k = \sum_{n=0}^{N-1} x_n\, e^{-i2\pi kn/N} \qquad k = 0, \ldots, N-1$$

This task is mainly for detecting tremor frequency f_r, average amplitude A_{avg_r} and maximum amplitude A_{max_r}. A distribution over frequency of the tremor data is calculated by FFT. The tremor frequency f_r is the weighted average of these frequencies. Average amplitude A_{avg_r} and maximum amplitude A_{max_r} are calculated by sliding window. The window is a period of time twice as long as the tremor cycle. By simply moving the window from the beginning to end of the whole testing period, the average amplitude and maximum amplitude of the current window can be calculated. And when the window comes to the end, there are two lists of average amplitude and maximum amplitude, the average value of the two lists are average amplitude A_{avg_r}

and maximum amplitude A_{max_r} separately. Sliding window is a good way to reduce the effects of sudden changes and errors in measurement. It will not make a difference if there is a false data point causing a sharp increase or decrease to the wave.

D. Postural Tremor

This task is mainly for detecting tremor frequency f_p, average amplitude $A_{avg_p}$and maximum amplitude A_{max_p}. Since in Postural Tremor part, the test subject is also required to hold the phone still, the feature extracting method is the same way as in Rest Tremor part.

E. Kinetic Tremor

This task is mainly for detecting the proportion of kinetic tremor over the whole movement p_k, average amplitude A_{avg_k} and maximum amplitude A_{max_k}.

Different from the Rest Tremor and Postural Tremor, the test subject's hand is not static but moving in a semi-circle motion in this test. So it is crucial to extract the tremor part from the mixes data. According to researches, the frequency of PD is 4-6 Hz. After doing FFT on the kinetic tremor data, if the frequency of the 4-6 Hz band accounts for a large proportion of the total distribution, it means that the PD kinetic tremor is severe. By doing inverse FFT over the frequency of the 4-6 Hz, a pure tremor wave can be obtained. Average amplitude A_{avg_k} and maximum amplitude A_{max_k} are calculated by sliding window, the same method used in the other two tremor tests.

F. Micrographia

This task is designed to detect micrographia among the test subjects. Since most patients with PD will write smaller letters of a sentence in the end than at the beginning, this task is an effective way to detect PD. To detect micrographia, we select the following features to analyse: 1) variance of tracking radius var_r; 2) average drawing angular speed in the entire period ω_a; 3) average drawing angular speed in the first-half ω_f and second-half ω_s. The first feature is for detecting micrographia and the others are used for bradykinesia and early fatigue separately.

We track the position of the test subject's finger and record the position 30 times per second to ensure the fidelity of the data. A pattern between the finger's position and the center of the screen can be provided by calculating the distance between the finger's position and the center of the screen. A slope var_r can be obtained by roughly considering the pattern as linear relationship, which represent the slowing up speed of the finger. If the test subject is a PD patient, var_r is more likely to be negative because of micrographia, otherwise, var_r is about 0 since that the test subject is able to track the original circle at the beginning and will not fluctuate a lot. The angular speed is calculated by inverse cosine theorem.

$$\theta = \arccos \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|} \tag{1}$$

where v_1, v_2 are vectors from the center of the screen to two finger positions that are close in time, and θ is the angle between them.

G. Coordination

Considering the normal subjects will complete the task faster and with less winding than the patients, we detect the 1) total drawing time t_{t_c}, 2) drawing length l_{t_c} and 3) drawing speed of the test subject v_{t_c}. Besides, we also collect 4) the sum of the left and right hands deviation d_{t_c} to recognise coordination.

Drawing length l_{t_c} is the total length of the test subject's drawing trails. Base on the same trails, PD patient's track is more likely to be longer than others since the tracks are more winding. Besides, the drawing speed of the test subject v_{t_c} is also slower than others because that test subjects may stop a lot and have difficulties to finish the draw smoothly. The sum of the left and right hands deviation d_{t_c} is a key point for coordination. The tracking frequency of the test subject's finger position is 30 times per second. Assuming that (x_{i_l}, y_{i_l}) and (x_{i_r}, y_{i_r}) are at the i th record, and (x_0, y_0) is the coordinate of the screen center,

$$d_{t_c} = \sum_{i=1}^{n} \left| |x_{i_l} - x_0| - |x_{i_r} - x_0| \right| + |y_{i_l} - y_{i_r}| \tag{2}$$

where n is the total tracking times. $|x_{i_l} - x_0|$ and $|x_{i_r} - x_0|$ are the distance between the fingers to center vertical line of the screen. So $\big||x_{i_l} - x_0| - |x_{i_r} - x_0|\big|$ is for detecting left and right hands' difference on the x-axis and $|y_{i_l} - y_{i_r}|$ is on the y-axis.

H. Finger Tapping

This task is mainly for detecting rigidity, early fatigue, bradyskinesia and movement coordination. So we use the features listed as follows to analyse: 1) total number of taps T_{t_f}; 2) number of valid taps T_{v_f}; 3) average finger moving speed v_{a_f} and distance d_{a_f} in the entire period; 4) average finger moving speed v_{f_f}, v_{s_f} and distance d_{f_f}, d_{s_f} in the first-half and the second-half.

Finger Tapping is a process that the test subject's two fingers move from the opposite corner to the center of the screen, so any movement towards the center is viewed as a tap. However, only when the final position of two fingers are inside the invisible circle centered on the center of the screen and radiused by the length we designed, can the tap be valid. Assuming the total moving distance is d_{t_f} and the total time is t_{t_f},

$$d_{a_f} = \frac{d_{t_f}}{T_{t_f}} \tag{3}$$

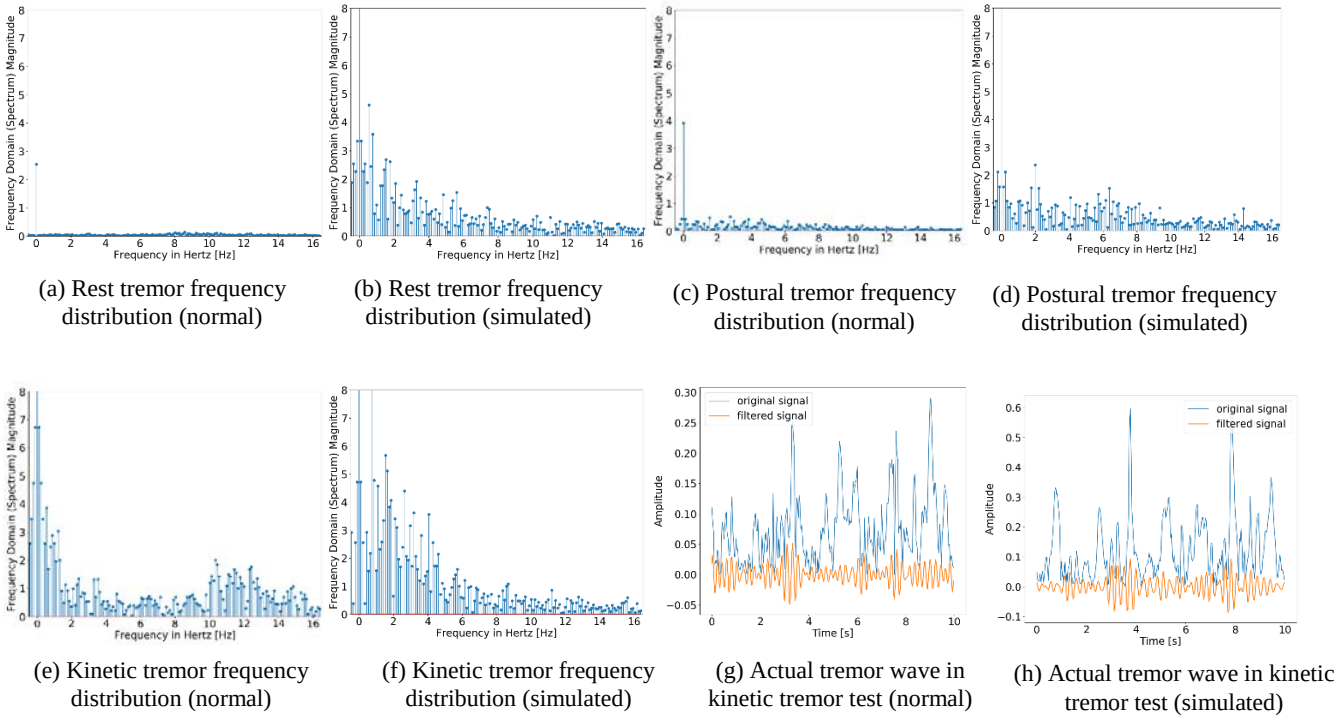
$$v_{a_f} = \frac{d_{t_f}}{T_{t_f} \cdot t_{t_f}} \tag{4}$$

v_{f_f}, v_{s_f}, d_{f_f} and d_{s_f} are obtained by dividing the total taps equally into the first-half and the second-half and calculated the same way as d_{a_f} and v_{a_f}.

V. Data Analytics

We simulated the PD patient's testing data in order to examine and improve our classification method. After learning the early PD symptoms thoroughly, the test subjects in the simulation group behaved slower and easier to get tired than their normal time. 5 normal testing results and 5 simulated ones are collected for data analytics. The features extracted from the data show significant differences from the two groups.

Figure 2 shows the differences of the normal and simulated group in the test for the three kinds of tremor after processed by FFT. Figure 2(a) and Figure 2(b) display the frequency distribution of the



(a) Rest tremor frequency distribution (normal)

(b) Rest tremor frequency distribution (simulated)

(c) Postural tremor frequency distribution (normal)

(d) Postural tremor frequency distribution (simulated)

(e) Kinetic tremor frequency distribution (normal)

(f) Kinetic tremor frequency distribution (simulated)

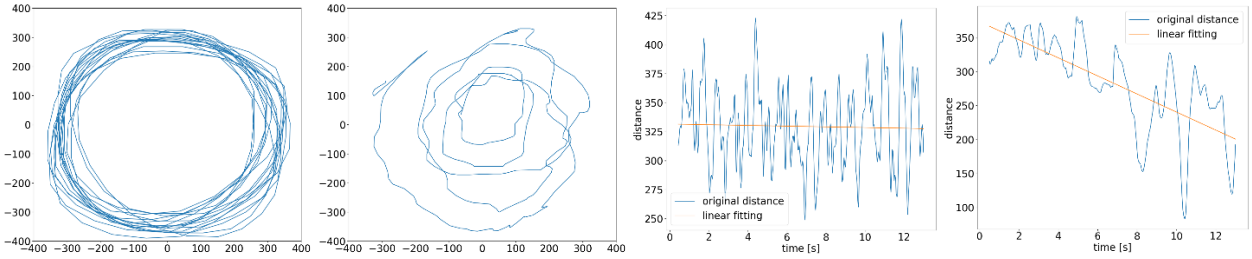
(g) Actual tremor wave in kinetic tremor test (normal)

(h) Actual tremor wave in kinetic tremor test (simulated)

Figure 2: Tremor testing result of normal subjects (a,c,e,g) and simulated patients (b,d,f,h)

normal and simulated group separately, Figure 2(c) and Figure 2(d) are for the postural tremor. In the two kinds of tremor, the frequency domain magnitude is much bigger in Figure 2(b) and Figure 2(d) than in Figure 2(a) and Figure 2(c) in every frequency band, which means that the simulated group has intenser tremor than the normal group. In the meanwhile, according to Figure 2(b) and Figure 2(d), the rest tremor is more severe than the postural tremor in the simulated group, which is based on the fact that rest tremor is the most affected symptom of PD. Besides, the features extracted from the testing result also show that the two group's tremor amplitude differ a lot. In the rest tremor part, the average amplitude A_{avg_r} is 0.008 for the normal and 0.063 for the simulated group, and the maximum amplitude A_{max_r} for the normal and simulated are 0.014 and 0.191, respectively. In the postural tremor test, the average amplitude A_{avg_p} is 0.014 for the normal and 0.042 for the simulated group, and the maximum amplitude A_{max_p} for the two groups are 1.33 and 0.122, respectively. The two pairs of amplitude for the simulated group also indicates that the tremor is more severe in the rest part than others.

In the tests for kinetic and postural tremor, the test subjects were instructed to hold their hands still. Hence, the tremor frequency can be directly extracted from the raw data. However, in the test for kinetic tremor, the test subject's hand moves in a semi-circle motion. Figure 2(e) and Figure 2(f)



(a) Drawing trail (normal) (b) Drawing trail (simulated) (c) Drawing radius over time and linear fitting line (normal) (d) Drawing radius over time and linear fitting line (simulated)

Figure 3: Micrographia testing result of normal subjects (a,c) and simulated patients (b,d)

present the frequency distribution of the normal and simulated group. In the two figures, the frequency domain magnitude is larger than the ones in Figure 2(a)-(d) because of the hand movement.

The tremor in Parkinson's disease is characterized by a frequency of 4 to 6 Hz. By extracting the waves with frequency between 4 to 6 Hz, the actual tremor wave can be obtained. Figure 2(g) and Figure 2(h) show the pure tremor wave in the postural tremor test. In these distributions, the portion of frequency between 4-6 Hz is much bigger in the simulated group than in the normal group, indicating that the PD tremor is more serious. Besides, calculated by sliding windows, the average amplitude A_{avg_k} of the pure tremor wave for the normal and simulated group are 0.013 and 0.023 separately, and the maximum amplitude A_{max_k} are 0.030 and 0.058, suggesting that the simulated group's tremor amplitude is bigger regardless of the hand movement.

Figure 3 displays the performance of the two groups in the Micrographia test and the analytics for it. In Figure 3(a), the circle is stable in size and the track is smooth, while in Figure 3(b), the circle is getting smaller and the track is winding. As consequence, the slope of the distance over time relationship for the normal group is around 0, while the slope for the simulated group is negative. As shown in Figure 3(c), the variance of tracking radius var_r is -0.311 pix/s, while in Figure 3(d), the slope var_r is -20.750 pix/s, whose absolute value is way much bigger than the former, meaning that the

distance from the finger position towards the center has a descending trend. Besides, the average angular speed of the two groups and the angular speed of the first-half and second-half are also calculated to analyze the testing result. In the normal group, the average angular speed ω_a is 8.648 rad/s, while in the simulated group, ω_a is only 2.609 rad/s. The angular speed in the first-half and the second-half of the control group are 8.797 rad/s and 8.499 rad/s separately, which in the intervention group, are 2.992 rad/s and 2.227 rad/s, meaning that the former speed drops by 3.39% while the latter one drops by 25.57%.

Besides, there are a lot of differences between the two groups. For instance, in the tapping test, the simulated group is of lower velocity and easier to get early fatigue. Moreover, in the coordination test, the simulated group take longer time to finish the tracking and the sum of the left and right hands deviation d_{t_c} is also bigger.

In order to distinguish the normal and the PD patient, we use support-vector machine (SVM) together with bagging algorithm as our classification model, which enable to classify the dataset with about 25 features to high-risk group and low-risk group. SVM constructs a hyperplane or set of hyperplanes in a high- or infinite- dimensional space. Bagging, also called bootstrap aggregating, is a machine learning ensemble meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression. Taking advantage of the two powerful machine-learning techniques, the classifier distinguishes the two groups with high accuracy.

VI. Conclusion

Parkinson's disease is a leading neurodegenerative disorder that threatens the living quality of older adults. Early diagnosis and treatment are crucial for delaying the deterioration of the nervous system caused by PD. To achieve this goal, long-term and frequent assessments are vital.

In this paper, we proposed a self-assessment platform on smart- phones to facilitate patients and caregivers to objectively screen PD symptoms and monitor the effectiveness of treatments in a home-based environment. This platform uses 9 mini-tests, designed in the light of the motion assessment

tasks of the Unified Parkinson's Disease Rating Scale (UPDRS), to evaluate the risk of developing PD. After studying the symptoms of PD thoroughly, we defined several features that are computed from data collected in each mini-test. By analyzing these features by SVM together with bagging algorithm, the test subjects are classified into high-risk group or low-risk group according to their test performance. We simulated the PD patient's testing data in order to examine and improve our classification model. With easily accessible tests and automatic data analytics, the home-based self-assessment platform can help greatly with detecting early PD signs, monitoring PD symptoms and providing longitudinal assessments for the users.

In the future, we will first conduct user studies with healthy young and older adults. The results obtained will be used to improve the usability and classification model of the platform. After obtaining the ethics approval, we will then conduct a long-term user study with healthy older adults (control group) and PD patients (intervention group) to evaluate the effectiveness of the proposed platform and the accuracy of the classification algorithm.

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