Efficacy of Guided Spiral Drawing in the Classification of Parkinson's Disease

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***Abstract*—Background: Change of handwriting can be an early marker for severity of Parkinson's disease but suffers from poor sensitivity and specificity due to inter-subject variations. Aim: This study has investigated the group-difference in the dynamic features during sketching of spiral between PD and control subjects with the aim of developing an accurate method for diagnosing PD patients. Method: Dynamic handwriting features were computed for 206 specimens collected from 62 Subjects (31 Parkinson's and 31 Controls). These were analyzed based on the severity of the disease to determine group-difference. Spearman rank correlation coefficient was computed to evaluate the strength of association for the different features. Results: Maximum area under ROC curve (AUC) using the dynamic features during different writing and spiral sketching tasks were in the range of 0.67 to 0.79. However, when angular features (φ and p_n) and count of direction inversion during sketching of the spiral were used, AUC improved to 0.933. Spearman correlation coefficient was highest for φ and p_n. Conclusion: The angular features and count of direction inversion which can be obtained in real-time while sketching the Archimedean guided spiral on a digital tablet can be used for differentiating between Parkinson's and healthy cohort.**

***Index Terms*—Parkinson's, dynamic feature, pen-pressure, kinematic features.**

I. Introduction

STIFFNESS, bradykinesia, and tremor are motor symptoms associated with Parkinson's disease (PD). These affect the writing and sketching abilities of the patients causing three changes; the size of writing [1], kinematics, and pen-pressure [2]. Often the size of the handwriting of PD patients is reduced which is referred to as Micrographia [3] and has been proposed as an early stage marker of the disease [4]. However, the handwriting of a person gets influenced by a number of factors like visual feedback and cueing which make the patients artificially adjust their handwriting during the test which makes the results unreliable [5], [6]. An alternative is the measure of the dynamics such as reduction in speed and Pen-Pressure during writing [2], [7] but these also suffer from poor reliability because of large inter-subject variability and other factors such as writing style, language skills and the body of the text itself [8].

An alternative option to handwriting is the use of patient's drawing abilities, especially recording the dynamics while the patients draw a spiral [9], [10]. However, Drotár *et al.* (2013) compared different writing task and found spiral showing poor correlation compared to other tasks [11]. The other difficulty is that the results are sensitive to the placement of the center point of the spiral [12] and have the overhead of detecting center [13].

The aim of this work was to identify the most suitable writing tasks and handwriting features where the difference between the severity based groups is significant. This paper reports the results from an investigation of the group-difference in the dynamic handwriting features of PD patients grouped based on the severity of the disease and control subjects for multiple handwriting and spiral drawing tasks.

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II. Materials and Methods

A. Recording Equipment

Wacom A3 size digital tablet (Wacom Intuos Pro Large) with ink-pen having pressure-sensor was used to record the dynamics of the handwriting. This device was selected because it gives a natural pen-paper feel to the patients, is large enough for the convenience of the elderly subjects and pilot study showed reproducibility of the results. This device records the point of contact (x, y) and pen pressure (pr) between the pen and the tablet which was recorded at 133 Hz of sampling rate and analysed in real-time to obtain the dynamics using the customized software. The placement and position of the tablet were adjusted such that the participants were comfortable in writing on it.

B. Subjects

The experimental protocol was approved by RMIT University Human Research Ethics Committee and in accordance with Helsinki Declaration (revised 2004). All participants provided their oral and written consent before the start of the experiment. The severity of the disease was measured by an expert neurologist using Unified Parkinson's Disease Rating Scale (UPDRS) Section III [14].

TABLE I
DEMOGRAPHIC AND CLINICAL INFORMATION OF THE PARTICIPANTS

Demographics	PD	Control Group
Number of Subjects, n	31	31
Age, years	70.1 ± 9.79	72.87 ± 6.5
Gender male, female	24,7	24,7
Handedness Right, Left	31,0	31,0
Disease duration, years	5.74 ± 4	–
UPDRS-III [0–56]	17.03 ± 7.13	–

62 age-matched volunteers ranging from UPDRS = 0 (control group) to severely affected patients (UPDRS > 24) were studied. All PD patients were recruited from the outpatient clinic at Dandenong Neurology, Melbourne, Australia. The control group subjects were recruited to approximately match the age distribution and gender of the PD patients from multiple aged-care facilities using word-of-mouth and appropriately located posters. All subjects were right-hand dominant. The exclusion criterions were: (i) clinically observed or self-reported skeletal injuries, (ii) neurological and muscular-skeletal diseases (other than Parkinson's) and (iii) excess Levodopa medication causing dyskinesia. For the PD patients who were on levodopa treatment, experiments were conducted while they were in the "On" stage. The UPDRS and severity of PD are as observed at the time of the experiment. The demographic and clinical data are shown in Table I.

C. Handwriting Task

Proprietary software was developed using c# programming language to record and analyze the data in real-time. The sampling rate was 133 Hz and the recorded data contains the following information:

1) Location (x, y) with x_n and y_n corresponding to the nth sample.
2) Pen-pressure (pr) recorded in the non-scaled unit by the pen (0–1023) and
3) Sample number, n.
4) Time stamp, t

Handwriting specimens were obtained for four different tasks which were selected based on works reported in the literature;

1) Task 1: Reproducing a sentence [15], [11],
2) Task 2: Repeating the characters individually; '*b*' and '*d*' multiple times [16],
3) Task 3: Repetitive writing of '*bd*' [11], and
4) Task 4: Sketching an Archimedean guided spiral [9], [17].

However, due to issues such as lack of fluency in writing in English, some participants were unable to complete all the tasks. Table II gives the number of participants who completed each respective task and shows examples of the tasks where the color red in sample image indicate more pen-tip pressure is applied (≥ 512 unit) whereas blue indicate pen-tip pressure was less (< 512 unit).

D. Dynamic Feature Calculation

The data was segmented to identify segments between each pen-down and corresponding pen-up; pen-down identified based on $pr > 0$, and given an index label, i with m_i being the total number of samples of the segment. The total length of each segment, d_i, was computed using (1) and segments of length less than 0.5 mm of distance traveled were considered as noise and deleted [18], no other smoothing was performed on the segments.

$$\boldsymbol{d_i} = \sum_{\mathbf{n}=0}^{\boldsymbol{m_i}} \sqrt{(\mathbf{x_{n+1}} - \mathbf{x_n})^2 + (\mathbf{y_{n+1}} - \mathbf{y_n})^2} \tag{1}$$

The remaining N segments and parameters were relabeled, i (1 to N) and used to compute the dynamic features that are shown in Table III. Four of these features; D_x, D_y, p_n and φ were only considered for the spiral sketching which are based on angle of drawing and requires drawing of constant size, hence were not suitable for other writing tasks; Task1 to Task 3.

E. Data Analysis

The flowchart showing the data analysis procedure is shown in Fig. 1. The data were analyzed using the following methods:

1) Feature Selection: Ten features (1–10) listed in Table III were used for analysis of the dynamics of the handwriting for all the 4 tasks. Spiral is associated with angle hence fluctuation in spiral drawing can be captured using direction D_x, D_y and angular feature φ, p_n. However these 4 features were not considered for tasks 1–3, as inter-personal variability and factors such as writing style and the text itself can influence the angle and direction due to which the inter-experimental variability is very large. All the 14 features were used only for Archimedean Guided Spiral Task which, due to the guiding dots reduced such variability. The next step was selection of appropriate features to understand the group difference. This is not only important for classification but for neurologists to better understand the disease and essential step for dynamic writing analysis [19]. This study has used Relief-F feature selection methods using Orange 3.3 data mining suite [20], [21] to rank and select the best five features.

2) Classification: The five selected features were classified using Naïve Bayes Algorithm [22] and validated using Random sampling algorithm with 80% of the data used for training and balance for testing. The stratified Random sampling strategy was used and the procedure was repeated 20 times. The recall, specificity, and accuracy of classification were computed to generate the receiver operating characteristics (ROC). The area under the curve (AUC) for ROC, precision, weighted average (F1) and Error Rate (ERR) were also computed.

3) Correlation: Correlation analysis was performed to study the strength of association between each feature for the four writing tasks. Spearman rank-order correlation coefficient analysis was performed to distinguish between PD and CG. The correlation analysis was performed using IBM SPSS statistical software.

III. RESULTS

Table IV shows the highest ranked features obtained using Relief-F feature selection method. As tabulated in Table IV Archimedean Guided Spiral Task with angle and direction fea-

TABLE II
DETAILS OF THE TASKS PERFORMED

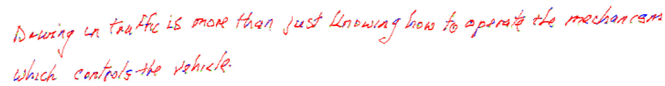
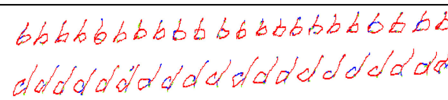
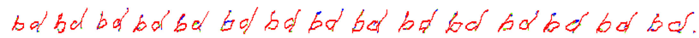
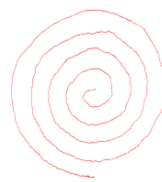
Task No.	Task Details	Groups(PD/CG)	Sample Image recorded from PD Patient
1	Reproducing a sentence	20/20	
2	Repeating the characters individually; '*b*' and '*d*' multiple times	28/28	
3	Repetitive writing of '*bd*'	29/29	
4	Sketching an Archimedean guided spiral	26/26	

TABLE III
NORMALIZED DYNAMIC FEATURES USED FOR DIFFERENT WRITING TASKS

Features	Description
s	The average speed of pen tip while it is moving on the surface.
$\bar{v}_x$	Rate at which pen tip changes its position in x-direction; Pen tip velocity in x-direction
$\bar{v}_y$	Rate at which pen tip changes its position in y-direction; Pen tip velocity in y-direction
$v/v_{\max}$	Magnitude of rate at which pen tip changes its position in x and y-direction divided by maximum velocity
SD (v)	Standard Deviation of velocity
a_x	The rate at which pen tip velocity changes in x-direction
a_y	The rate at which pen tip velocity changes in y-direction
$a_{\max x}$	Maximum acceleration of pen tip in x-direction
$a_{\max y}$	Maximum acceleration of pen tip in y-direction
pr	Pen tip pressure applied on the surface [Range:0–1023]
D_x	Number of time direction changes in x-direction
D_y	Number of time direction changes in y-direction
φ	Arctangent (ATAN2) which is an angle in radians between the positive x-axis of a plane and the point given by the coordinates (x, y) on it.
p_n	Logarithmic value of distance traveled by pen divided by φ

tures referred as 4b shows the 3 angular and direction features: φ, p_n and D_x in top 5 features. Table V shows five measures of classification for the four tasks. It is observed that AUC for all the four tasks is roughly in similar range (range 0.67 to 0.79), with the order being Task 2 (Repeating the characters individually), Task 4a (Archimedean Guided Spiral Task), Task 1 (Reproducing a sentence), and Task 3 (Repetitive writing of '*bd*'). However, classifying with the 4 angular and directional features could only be performed for Task 4 (Archimedean Guided Spiral Task) and is referred to 4b; D_x, D_y, p_r and φ, the results are significantly better, with AUC $= 0.933$.

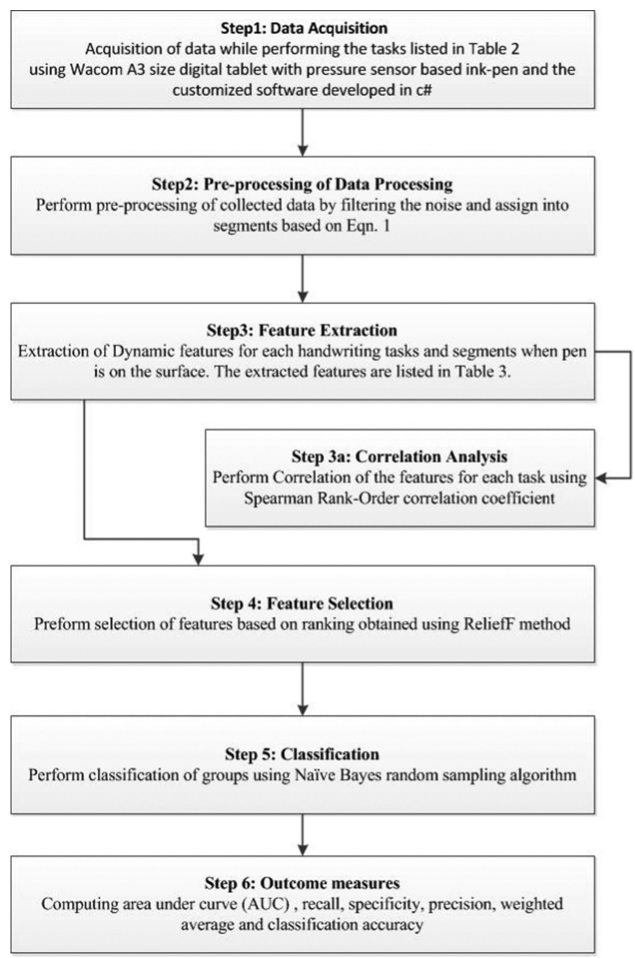


Fig. 1. Flowchart showing the data analysis procedure.

A. Correlation Analysis

Table VI shows the Spearman rank-order correlation coefficient for each feature and task for PD group. Coefficients having a significant correlation at p $<$ *0.05* have been highlighted. The results show that the highest correlation is for the angle φ from Task 4b. Task 2, Task 3 and Task 4a shows correlation in the range of $(0.4 < r_s < 0.59)$ for a_y, a_y and p_r respectively

TABLE IV
FIVE HIGHEST RANKED FEATURES SELECTED USING RELIEF-F FEATURE SELECTION TECHNIQUE

Tasks	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5
1	pr	$\bar{v}_y$	a_y	SD (v)	s
2	pr	$a_{\max x}$	SD (v)	$\bar{v}_x$	s
3	a_y	SD (v)	s	$v/v_{\max}$	$a_{\max y}$
4a	pr	$\bar{v}_y$	$\bar{v}_x$	$v/v_{\max}$	s
4b	pr	φ	p_n	D_x	$a_{\max y}$

where Task 4a and Task 4b represent Archimedean Guided Spiral Task with 10 and 14 features respectively.

TABLE V
CLASSIFICATION BY NAÏVE BAYES ALGORITHM BASED ON 5 HIGHEST RANKED FEATURES

Tasks	AUC	CA	F1	Precision	ERR
1	0.748	0.681	0.648	0.688	0.319
2	0.787	0.738	0.693	0.760	0.263
3	0.671	0.704	0.643	0.731	0.296
4a	0.767	0.677	0.654	0.678	0.323
4b	**0.933**	**0.832**	**0.826**	**0.832**	**0.168**

TABLE VI
SPEARMAN RANK-ORDER CORRELATION COEFFICIENT ANALYSIS OF PD AND CG FOR EACH FEATURE AND EACH TASK

Features	Task 1	Task 2	Task 3	Task 4
$\boldsymbol{s}$	−0.273 *(0.088)*	-0.331^{*} *(0.013)*	-0.390^{**} ***(0.002)***	-0.405^{**} ***(0.003)***
$\bar{\boldsymbol{v}}_{\boldsymbol{x}}$	−0.264 *(0.099)*	-0.267^{*} *(0.046)*	-0.285^{*} *(0.030)*	-0.400^{**} ***(0.003)***
$\bar{\boldsymbol{v}}_{\boldsymbol{y}}$	−0.195 *(0.228)*	-0.378^{**} ***(0.004)***	-0.432^{**} ***(0.001)***	-0.420^{**} ***(0.002)***
$\bar{\boldsymbol{v}}/\boldsymbol{v}_{\max}$	−0.269 *(.094)*	-0.334^{*} *(0.012)*	-0.384^{**} ***(0.003)***	-0.397^{**} ***(0.004)***
SD $(\boldsymbol{v})$	−0.117 *(0.472)*	-0.360^{**} ***(0.006)***	-0.386^{**} ***(0.003)***	−0.272 *(0.051)*
$\boldsymbol{a_x}$	−0.256 *(0.111)*	-0.294^{*} *(0.028)*	-0.217^{*} *(<0.040)*	−0.256 *(0.067)*
$\boldsymbol{a_y}$	−0.251 *(0.118)*	-0.418^{**} ***(0.001)***	-0.460^{**} ***(<.001)***	−0.323 *(0.020)*
$\boldsymbol{p_r}$	−0.225 *(0.162)*	-0.360^{**} ***(0.006)***	-0.368^{**} ***(0.005)***	-0.525^{**} ***(<0.001)***
$\boldsymbol{a}_{\max \boldsymbol{x}}$	−0.100 *(0.541)*	−0.225 *(0.095)*	-0.298^{*} *(0.023)*	-0.323^{*} *(0.020)*
$\boldsymbol{a}_{\max \boldsymbol{y}}$	−0.022 *(0.894)*	-0.345^{**} ***(0.009)***	-0.394^{**} ***(0.002)***	-0.377^{**} ***(0.006)***
$\boldsymbol{D_x}$	NA	NA	NA	-0.495^{**} ***(<0.001)***
$\boldsymbol{D_y}$	NA	NA	NA	−0.038 *(0.785)*
φ	NA	NA	NA	-0.638^{**} ***(<0.001)***
$\boldsymbol{p_n}$	NA	NA	NA	-0.615^{**} ***(<0.001)***

r_s (P-values) values of Spearman Correlation coefficients, Correlation is significant at the $0.01\ level\ (2-tailed)^{**}$ and $0.05\ level\ (2-tailed)^{*}$, –ve values indicate correlation is negative.

whereas, task 4b (with $s, \bar{v}_x, \bar{v}_y,\ pr, D_x$) has stronger correlation $(r_s > 0.6)$ with p < 0.001 for φ and p_n $(2-tailed\ tests)$.

IV. DISCUSSION

Our study has investigated the use of dynamic handwriting features. When the traditional dynamic features were used, the results obtained is similar to those reported by Drotár *et al.* (2013). While this study found the repeating the letters to be more accurate, the difference between the different tasks was small. However, when a new set of features, the angle φ and p_n were considered, the AUC improved to 0.933 and the correlation was 0.638 and 0.615 with $p < 0.001$. This feature set was originally proposed by Sadikov *et al.* [23] to detect tremor. The advantage of this work is that it does not require any supervision and does not require the identification of the center point of the spiral.

Investigation of the choice of handwriting tasks for differentiating between severity of PD by Drotár *et al.* (2013) had determined that sketching of the spiral was least effective (0.65) while writing a sentence gave highest classification accuracy (0.787) [11]. In contrary, the results reported by Pariera *et al.* (2015) using spiral sketching were different and they achieved an accuracy of 0.78 using Naïve Bayes [24] while Sadikov *et al.,* achieved 0.895 [23]. However, a number of revolutions and size of the spiral can vary. In this study, we used fixed size spiral vs varying size spiral where results can be biased as patients try to manipulate writing size [25]. The system is not dependent on the location of spiral starting point [12]. Further, it helped to increase the efficacy by using $D \to (x)$ which also showed moderate correlation (>0.4) using Spearman's rank-order correlation coefficient.

In this study visually observed micrographia was found only in the patients with severe PD but we could not observe this in the rest. This is similar to the one reported by Ling *et al.* who reported micrographia was only noticed in 15% of PD patients [26]. In this study, we have observed that while there was significant difference in the dynamics of sketching between the PD and control subjects, there was no difference in the shape of spiral drawn by them, thereby highlighting the relevance of machine based diagnosis.

The strength of the method proposed in this study uses Archimedean guided spiral which overcomes the inter-experimental variations, potential bias due to manipulation of the size or number of revolution made by participant [27], incorrect center detection [12], and manipulation due to visual feedback [6]. It uses the dynamic features and does not require any input from the examiner. There is no requirement to identify the location of the origin point and the analysis is performed in real-time using an inexpensive digital tablet and paper. In previous study Archimedian guided spiral (AGS) was used to distinguish between different severity levels [18]. In this study AUC curve of 0.933 is obtained which shows that it can effectively differentiate between control group from PD patients.

Our study has also observed that while a number of PD patients and control subjects were unable to reproduce sentences in their own handwriting, all the participants were able to sketch the spiral. This shows that this method can be considered for diagnosing the disease and monitoring the progress of the disease, irrespective of the ethnicity, cultural background, language skills and level of education.

It is important to note that this study was conducted on patients in their "On" state of their medication. The results show that this method identifies significant differences between patients having different levels of severity of the disease and control groups even when they have active pharmacological treatment.

A. Limitations

There are two major limitations in this study; it has not studied patients in their "Off" state, and it is a group based cross-sectional study. There is the need to test patients in their "Off" state and perform the longitudinal study. When the patients are tested in the "Off" state, the relationship of this test with PD will be clearly established. Only then will it be evident that this method can be used for diagnosis or monitoring of the disease. It will also show the effect of medication on the handwriting of the patients.

Repetitive and longitudinal testing of the patients is necessary to validate the repeatability of the technique and its effectiveness for monitoring the patients in response to any intervention. For this, we are working with multi-center trials where we will be sharing the software with the partners.

V. Conclusion

This study has compared different writing task to obtain the difference of groups based on the level of severity of Parkinson's disease. It has shown that the use of Angular (φ and p_n) and Direction change features for Archimedean guided spiral were most suitable to distinguish between the PD and Control groups. Other advantages of using AGS were; language independent and suitable for unsupervised testing.

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