# NOVEL FEATURES FOR DIAGNOSIS OF PARKINSON'S DISEASE FROM OFF-LINE ARCHIMEDEAN SPIRAL IMAGES


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***Abstract*—Parkinson's Disease (PD) is difficult to diagnose and is commonly a diagnosis of exclusion. A common early symptom of PD is handwriting and/or drawing difficulty. Most of the early systems rely on on-line handwritten / hand-drawn data which need specialized equipments to capture. Such costly systems may not be available where infrastructural facilities are limited. So we intend to devise a low cost system for the same purpose. Towards the goal, in this paper we present novel distance based features to diagnose Parkinson's disease from off-line hand drawn Archimedean Spiral. We have tested our algorithm on a benchmark database $PaHaW$. Performance of our system is compared with that of some existing systems. Experimental results suggest that proposed feature works good and is better than existing systems.**



Archimedean Spiral, Fourier Tranform, distance, tremor


## I. Introduction

Parkinson's disease (PD) is a progressive neurological disorder that effects movement and is characterized by rigidity,tremor and bradykinesia. It is difficult to diagnose and is commonly a diagnosis of exclusion.Neurologists based on patient's clinical evaluation and imaging studies (such as MRI, CT and PET scans) of the brain rule out diseases with similar presentation. Even then, the probability of an inaccurate diagnosis is approximately 25% [12]. Till today cure of PD is not possible but an early detection is essential for restricting disease progression. Handwriting or hand-drawing is a complex activity that involves several cognitive sensory and perceptual motor components such as fine motor control and eye-hand coordination. A common early symptom of PD is handwriting/drawing difficulty.

Currently research works are focused on developing an automatic system for PD diagnosis from online handwriting samples using special writing kit (capable to record writing speed, pen pressure etc) [13], [17], [1], [15], [2], [14], [7], [5], [11]. They have analyzed stroke length, width, height, pen pressure, pen position, jerking intensity, writing speed etc to differentiate PD from healthy control. Drotar et. al have showed the performance of kinematic and pressure features of hand writing to differentiate PD patient and healthy person [3]. Mucha et. al have explored the impact of advanced online handwriting parameterization based on fractional-order derivatives (FD) [10]. Impedovo et. al have studied on to which extent dynamic features of the handwriting process can help PD diagnosis at earlier stages [6]. In contrast, Moetesum et. al have used Convolutional Neural Networks to extract discriminating visual features from writing samples and then fed to a Support Vector Machines (SVM) to classify PD patient and healthy controls [9]. Different type of classifiers like SVM, Bayesian Classifier (BC), Optimum-Path Forest (OPF) classifier etc. are used to develop automatic systems. Sometimes results of multiple classification methods are combined [2] or some feature selection techniques like crow search algorithm (OCSA) [5] are used to increase system performance. Sentore et al. [14] have applied Cartesian Genetic Programming (CGP) classification technique for their system. Zuo et al. [18] proposed a computer-oriented system to aid PD diagnosis based on Particle Swarm Optimization and fuzzy k-nearest neighbours classifier. There are two freely available benchmark online databases containing handwriting or drawing of PD patient as well as healthy controls, which are $HandPD$ database used in [14], [7], [5], [1], [11] and $PaHaW$ database used in [9], [6], [10], [3].

Most of the studies which focus on analyzing online hand writing or drawing need special writing kit which may not be readily available especially in developing countries. Making geometric patterns using spirographs is a standard method to test a persons handwriting/drawing capability and is used for diagnosing PD in early stage [13], [16], [4], [8]. So, we want to explore the possibility if the scanned images of off-line hand-drawn patterns can be used to diagnose PD. This paper present a novel distance feature based on two common early symptoms of PD: (i) tremor and (ii) micrographia (resulting in reduction of size of written patterns ) to identify PD patients from healthy ones. Presence of hand tremor may reflects in hand drawing as patients having tremor in hand cannot draw a smooth line, and whenever they try to follow smooth lines, they come up with some short zig-zag strokes around the smooth line as shown in Fig. 1 Left. As a result number of black pixel present in drawing is greater for PD patients having hand tremor with respect to healthy controls. Note that here we have considered not only tremor symptom but also some other early symptoms of PD, like bradykinesia, muscle stiffness, rigidity that results micrographia in spiral drawing, which may useful to differentiate PD from other tremor symptom disease. Very often due to muscle rigidity and bradykinesia, patients suffering from PD fail to maintain angle vs radial distance relation of Archemedean spiral. Thus small overlapping spirals with tightly bunched turns are observed in hand drawn Archemedean spiral for PD patient as shown in Fig 1 Right.

Rest of the paper is organized as follows: Proposed method is explained in Section II. In Section III detailed experimental set up, results and comparative study are explained. Finally, concluding remarks are placed in Section IV.

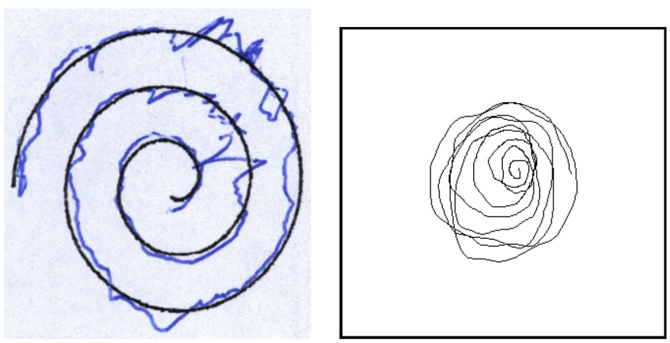

Fig. 1. Left: Noisy strokes appeared about reference Archimedean spiral hand tremor (taken from HandPD dataset)
Right: Micrographia is observed in some orientation of Archimedean spiral

## II. Proposed method

### A. Input

This paper proposes an automatic system to diagnose PD based on off-line hand-drawn Archimedean spiral. An Archimedean spiral can be represented in polar $(r, \theta)$ form as

$$r = a + b\theta \tag{1}$$

where 'a' and 'b' are real numbers, and angle $\theta$ varies indefinitely. Here parameter 'a' positions the spiral, and parameter 'b' controls the distance between any pair of points on the curve separated by $\theta = 2\pi$. Archimedean spiral is an open ended curve with two end points, one end point at interior to the curve where $\theta = 0$. We call it the *starting point* $(x_1, y_1)$, while the other end point as the *terminal point* $(x_n, y_n)$.

Each subject is requested to draw an Archimedean spiral in a given square box with a conventional ink pen by holding it in a normal fashion, allowing for immediate full visual feedback. There is no restriction on either numbers of turns or special writing posture or writing speed. These hand drawn spirals are the input to our proposed system for diagnosing and analyzing PD.

### B. Preprocessing

All scanned (digitized) images of hand-drawn Archimedean spiral are binarized using Otsu's thresholding algorithm. The binarized images are then cleaned by applying morphological opening and closing filters, and are thinned to one pixel width. Then starting point of each hand drawn spiral is determined. Now using spatial translation the starting point of the binarized and thinned hand-drawn spiral is placed at the center of the image. All translated images are, finally, brought to a common size using zero padding. Some example of such pre-processed images of hand-drawn Archimedean spiral are shown in Fig. 2.

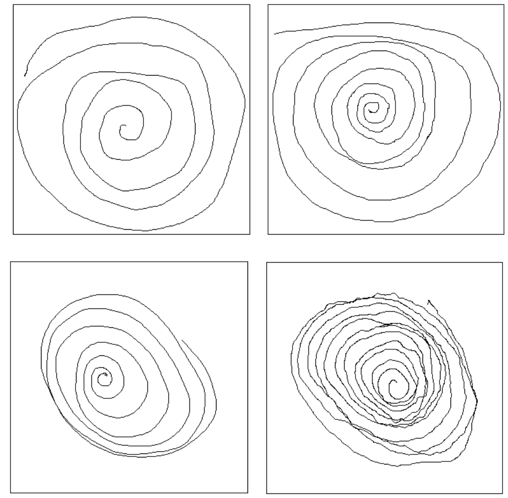

Fig. 2. Four pre-processed Archimedean spiral taken from $PaHaW$ database

### C. Feature extraction

This paper introduces two novel features extracted from off-line images $I(x, y)$ of hand-drawn Archimedean spiral to differentiate PD patients and healthy persons. A detail description of features extraction follows.

After pre-processing, the position of all black pixels $(x, y)$ are stored in a sequence $< \hat{S}_i = (x_i, y_i) \mid i = 1, 2, \ldots, n >$. Then those pixels are re-arranged to $< S_i = (x_i, y_i) \mid i = 1, 2, \ldots, N >$ as if traced along the spiral starting from $(x_1, y_1)$ as stated below. Note that $N \geq n$.

First, assuming 8-connectivity of black (object) pixels, each black pixel of $I(x, y)$ is characterized (i.e., labeled) by the count of black pixels in its nearest 8-neighbours as follows.

(i) Current pixel is a dot (or noise, in this case) if there is no black pixel in its neighbour. Assign label 'a'.
(ii) Current pixel is an end point if there is one black pixel in its neighbour. Assign label 'b'.
(iii) Current pixel is on continuous stroke if there are exactly two black pixels in its neighbour. Assign label 'c'.
(iv) Current pixel is a crossing pixel if there are more than two black pixels in its neighbour. Assign label 'd'.

The pixel position of end points (with label 'b') and crossing points (with label 'c') are stored in $P_{end}(j)$ and $P_{cross}(k)$. Though ideally an Archimedean spiral has two end points: starting point and terminal point, but in practice specially for the case of patient hand drawing, a number of end points may appear. Now euclidean distance from all end points to the centroid $C$ of input image are estimated and minimum distance end point is taken as the starting point of hand drawn spiral. The pixel position of starting point is stored in $S_1$, i.e.,

$$j^* = arg \min_j dist(C, P_{end}(j)) \quad (2)$$

and

$$S_1 = P_{end}(j^*) \quad (3)$$

Similarly, we can find terminal point.

Now we start from $S_1$ and trace along the spiral as follows.

(a) We move to neighbour of last pixel visited along the spiral and store the current pixel in $S_i$ and delete the current black pixel from $I(x, y)$, if its label is 'b'.
(b) However, If the current pixel label is 'c', we store it in $S_i$ but do not delete the current black pixel from $I(x, y)$ nor we delete the subsequent pixels (even if there labels are 'b') until we visit next the pixel with label 'c'. Then we go back to Step (a).
(c) We follow the step (a) or Step (b) depending on the situation until we encounter terminal point.

To ensure proper tracing along the spiral in case of crossing, overlap or excess juggedness we employ double check. This simply implemented computing distance of black pixels on the spiral along same $\theta$. In that case we take the pixel which is closest to starting point $S_1$, but do not delete the pixel from further consideration. Once $< S_i >$ is formed two distance feature vectors are estimated from this as explained below.

*1) Fourier Transform based distance feature:* In Archimedean spiral, radial distance $r$ increases smoothly with $\theta$ as shown in Eq.1. Due to muscle stiffness, bradykinesia and micrographia PD patient fails to maintain this smoothness which may be used to identify PD patient from healthy people. From objective measurement point of view, this smoothness may be captured through Fourier transform. Slow increment of $r$ with $\theta$ suggests that (from equation (1))

$$\Delta r = b\Delta\theta \quad (4)$$

So $\Delta r$ should be constant if $\Delta\theta$, which is the case here, and in that case Fourier transform coefficients should be non-zero (actually very high) value only at 0 frequency or, at most, at very close to zero frequency. On the other hand, jaggedness in the drawn spiral leads to large variation in $\Delta r$, which in turn contributes large values to high frequency components of Fourier transform. Proposed feature tries to capture this characteristics of change in radial distance with change in $\theta$ or time using Fourier Transform.

First, distances of elements in $< S_i >$ from starting point $S_1$ are computed, and are stored in $D$. It is expected that $D$ should contain monotonically increasing distances, and $D_i - D_{i-1}$ would give more or less constant values. This is true for healthy people, but not for PD patients suffering from hand tremor and micrographia. stored in $\delta$. Note that the length of $< \delta >$ is not fixed but varies from sample to sample. To handle this issue, we have sliced $\delta$ using non-overlapping window of width $K$ and applied $K$ point Fourier Transform on each slice. Finally, the frequency component-wise average of $K$ point Fourier Transforms of the slices is taken as feature. The algorithm for this feature is summarized below.

**Algorithm:** EXTRACTION OF FOURIER TRANSFORM BASED DISTANCE FEATURE
**Input:** Arranged black pixel sequence $< S_i >$
**Output:** Feature vector $F$.

step 1: Count elements in $< S_i >$ and store in $d$.
step 2: FOR $i = 1$ to $d$:
- Compute Euclidean distance of $S(x_i, y_i)$ from $(x_1, y_1)$ and store in an array $D$.

step 3: FOR $i = 1$ to $d - 1$:
- Compute Euclidean distance between $D(i)$ and $D(i + 1)$ and store in $\delta(i)$

step 4: Take an array $F = [f(\cdot)]$ having $K$ elements and initialize with 0 (zero) to save feature vector.
step 5: Take two array $A = [a(\cdot)]$ and $F_A = [a(\cdot)]$ having $K$ elements and initialize with 0 (zero) for temporary storage.
step 6: Initialize p with 1 (one).
step 7: FOR $i = 1$ to $d - 1$ with interval $t = ceil((d - 1)/K)$:
- FOR $j = 1$ to K:
- $A(j) = \delta(i + j - 1)$
- END FOR
- Take Fourier transform of A and store in $p^{th}$ row of $F_A$
- Increment p by 1
END FOR

step 8 : Take column wise average of $F_A$ and store in F

*2) Tremor Estimating distance based feature:* Compared to a healthy person, spiral drawn by a PD patient would take more number of black pixels to cover same coverage of $\theta$, say, $\theta_2 - \theta_1$. This has already been discussed from a different perspective. A person having tremors during writing is expected to follow more deviations from a smooth curve generated by healthy person while drawing a spiral. Based on this observation, this paper proposes another distance based feature, named *Tremor Estimating distance based feature*.

First, we select a constant distance $Q$ between two points on the spiral. Now suppose starting from an element $S_j$ of $< S_i >$ of the spiral, we count of traversed elements of $< S_i >$ sequentially until we reach an element $S_k$ such that $dist(S_j, S_k) = Q$. We store this count $C_j$ in $< C_i >$. Next start point for this operation may be $S_{j+m}$. We may vary both $Q$ and $m$. Note that this operation initiates from starting point of the spiral $S_1$. Finally, histogram of $C$ is taken as Tremor Estimating distance based feature. The algorithm for Tremor Estimation distance feature is summarized below.

**Algorithm:** EXTRACTION OF TREMOR ESTIMATION DISTANCE FEATURE

**Input:** Arranged black pixel sequence $< S_i >$
**Output:** Feature vector $F$.

step 1: Count elements in $< S_i >$ and store in $d$.
step 2: Take $Q$ as a constant distance
step 3: Initialize $p = 1$ to store starting point index
step 4: Initialize $i$ with zero
step 5: Initialize $count$ with zero
step 6: Take an array $C$ to store $count$
step 7: Take an array $F = [f(\cdot)]$ having $L$ elements and initialize with 0 (zero) to save feature vector.
step 8: WHILE $i < d$

- FOR $i = p$ to d:
- Calculate distance of $S(x_i, y_i)$ from $S(x_p, y_p)$ and save it to $q$
- If $q \leq Q$ :
- $count$ is incremented by 1
- Else:
- Store $count$ in $C$
- p=i
- Break
- END IF
- END FOR

END WHILE
step 9: Take Histogram of $C$ and save in feature vector $F$

Finally we have concatenated Fourier Transform based distance feature and Tremor Estimation based distance feature to form combined feature. Then combined feature vector is fed to a suitable classifier. In this paper we have taken suitable support vector machine (SVM) for classification.

## III. Experiments

All experiments reported in this paper are done on $Intel®Core^{TM}\ i7-4790CPU\ @3.60GHz \times 8$ using Python 3. Proposed algorithm is tested on a benchmark online database of hand drawn patterns for PD diagnosis, named Parkinson's Disease Handwriting Database ($PaHaW$).

### A. PaHaW database

This database consists of multiple handwriting samples from 37 PD (19 men/18 women) and 38 gender and age matched healthy person (20 men/18 women). The samples were collected from the Movement Disorders Center at the First Department of Neurology, Masaryk University and St. Anne's University Hospital in Brno, Czech Republic. Each subject was asked to complete eight handwriting tasks at a comfortable speed. A tablet was overlaid with an empty paper template (containing only printed lines and square box specifying area for Archimedean spiral), and a conventional ink pen was held in a normal fashion, allowing for immediate full visual feedback. The signals were recorded using the Intuos 4M (Wacom technology) digitizing tablet with 150 Hz sampling frequency. The tablet captured the following dynamic features (time-sequences): x-coordinate; y-coordinate; time stamp; button status; pressure; tilt; and elevation. Button status is a binary variable, being 0 for pen-up state (in-air movement) and 1 for pen-down state (on-surface movement). For this experiment, we have used only Archimedean spiral. The dataset is freely available in $https://bdalab.utko.feec.vutbr.cz/$ Note that this database does not contain off-line hand trace of drawing or writing. Thus to construct off-line spiral from aforementioned dynamic feature, we have connected the location (x-coordinate, y-coordinate) of pen having button status 1 ( for pen down state). These Archimedean spirals are used for our experiment. As this database does not contain a fixed partition for training and test set, we have randomly selected 90% of patients and 90% of healthy subject to form training set. and rest 10% of each group are used to form test set. These partition is done for 20 iteration and all results reported here the average of 20 runs.

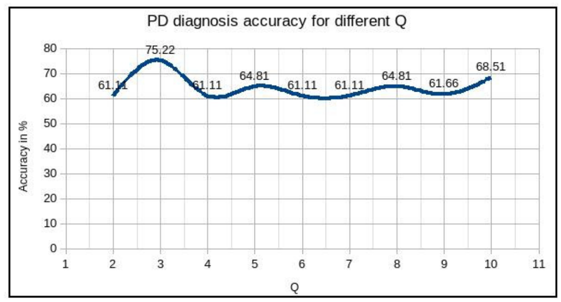


Fig. 3. PD Diagnosis accuracy for different $Q$. Optimum Q is set as 3.

### B. Parameter setting

In our experiment, we have resized all Archimedean spirals into an common size $(maximum\ \ length \times maximum\ \ breath)$ of all images which is $(318 \times 334)$. For Fourier Transform based distance feature estimation K is taken as 256, thus feature dimension of Fourier Transform based distance feature is 256. Again for Tremor Estimation distance feature we have to select an optimum constant distance $S$. For that, we vary $Q$ from 2 to 10 in step 1 and estimate the diagnosis accuracy for tremor estimation distance feature. PD diagnosis accuracy for different $Q$ are shown in Fig-3. Best diagnosis accuracy is achieved for $Q = 3$, thus optimum Q is set as 3. For Tremor Estimation distance feature we have selected $L = 15$ as maximum value of $C$ for used database is 15. Thus the feature dimension of Tremor Estimation distance feature is 15 respectively. In our experiment, we have chosen sigmoid kernel based SVM for Fourier Transform based distance feature and radial basis function kernel based SVM for Tremor Estimation distance feature. We have performed 10-fold cross validation technique to set the regularization parameter $c$ and $gamma$ of SVM corresponding to the best performance.

### C. Result

The performance of proposed system is measured in terms of $Accuracy$, $Precision$, $Recall$ and $F\ measure$. As our objective is to diagnose PD patient thus our target (or positive) class is patient class. The $Precision$, $Recall$ and $F\ measure$

TABLE I
DISEASE DIAGNOSIS ACCURACY OF DISTANCE FEATURE (TARGET CLASS: PATIENT)

| Feature vector | Kernel of SVM | Accuracy (%) | Precision | Recall | F measure |
|---|---|---|---|---|---|
| Furier Transform based distance feature | Sigmoid | 79.63 | .86 | .74 | .76 |
| Tremor Estimation distance feature | RBF | 75.92 | .84 | .78 | .76 |
| Combined feature | Sigmoid | 81.66 | .91 | .74 | .80 |

TABLE II
PERFORMANCE COMPARISON FOR ARCHIMEDEAN SPIRAL TESTED ON $PaHaW$ DATABASE

| Author (year) | Feature | Classifier (%) | Accuracy (%) |
|---|---|---|---|
| Moetesum et al.[9] (2019) | CNN extracted feature | SVM | 76 |
| Impedovo et al.[6] (2018) | Dynamic feature | Gaussian Naive Bayes | 54.67 |
| Drotar et al.[3] (2016) | Kinematic and Pressure feature | SVM | 62.80 |
| Proposed | Fourier Transform based feature | SVM | 79.63 |
| Proposed | Tremor Estimation feature | SVM | 75.92 |
| Proposed | Combined distance feature | SVM | 81.66 |

are explained in terns of true positive (TP), false positive (FP), true negative (TN) and false negative (FN) are given by

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (5)$$

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

$$F\ measure = \frac{2 \times Precision \times Recall}{Precision + Recal} \quad (8)$$

Experimental results for Fourier Transform based distance feature, Tremor Estimation distance feature and Combined feature is reported in Table-I. It is observed that proposed Fourier Transform based distance feature works better than Tremor Estimation distance feature and combined feature which is the concatenation of two features can be used to improve performance of individual feature.

We have compared our experimental results with three existing automatic system for PD diagnosis from Archimedean spiral tested on $PaHaW$ database. The comparison is reported in Table-II. Note that all works reported here, have followed same experimental protocol. The comparative study shows that the proposed off-line system can diagnose PD from healthy group better than existing systems tested on $PaHaW$ database.

## IV. CONCLUSION

This paper introduces an automatic PD diagnosis system using off-line hand-drawn Archimedean spiral. Proposed system shows improvement over the recently proposed methods for diagnosing PD. More importantly, unlike other methods we do not use on-line data (which supplement more information about handwriting). As only the scanned version of hand-drawn spiral is used as input for our system, it doesn't need any special writing kit for online handwriting analysis thereby reducing the effective cost of the diagnosis system compared to online systems. So the proposed system is more suitable where there is limited infrastructure.

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