



Detecting Huntington Patient Using Chaotic Features of Gait Time Series

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Abstract

Huntington's disease (HD) is a congenital, progressive, neurodegenerative disorder characterized by cognitive, motor, and psychological disorders. Clinical diagnosis of HD relies on the manifestation of movement abnormalities. In this study, we introduce a mathematical method for HD detection using step spacing. We used 16 walking signals as control and 20 walking signals as HD. We took a step back from the walking distance signals. Then, using fractal dimensions and statistical features, the control was classified and HD and 97.22% accuracy were obtained.

Keywords: HD, Gait Signal, Stride Time Interval, Fractal Dimension, Statistical Features

1. Introduction

Huntington's disease (HD) is an inherited neurodegenerative disorder caused by the proliferation of three CAG series repeats in the Huntington's gene on chromosome 4, which results in the production of a protein with an abnormal polyglutamine sequence [1]. The normal function of the Huntington's protein is unknown. Neuropathology indicates the loss of moderate GABAergic prickly neurons, a deficiency of large cholinergic interneurons, and the loss of specific neurons in layers V and VI of the cerebral cortex [2, 3]. Morphometric analysis of MRI shows marked atrophy in the thinning of the cortical ribbon striatum, and evidence of white matter volume loss [4, 5].

The clinical diagnosis of HD is based on neurological evaluation showing an additional pyramidal movement disorder without ambiguity. Those who have been genetically engineered to develop the HD gene [6] but do not yet show significant motor symptoms are in the pre-production stage of HD [7, 8].

In the following sections, we will first introduce the content and topics, then describe the features, and finally classify the two groups of control and HD.

2. Materials and Methods

2.1 Signals

To examine Huntington's disease, we use Gait in the Neurological Database of Physionet.org, which includes 20 Huntington's disease walking signals and 16 normal

walking signals as control signals with a sampling frequency of 300 Hz. These signals indicate the force of walking on the right and left feet as shown in Figure 1.



Figure 1. A sample of gait signal on right and left foot

As shown in Figure 1, when the right foot is the point of support, the force on the right foot is positive when walking, and the force on the left foot is negative, and vice versa. While in this study we want to examine the time interval of the step and using these walking signals we took the step time. An example of a normal walking time with Huntington is shown in Figure 2.

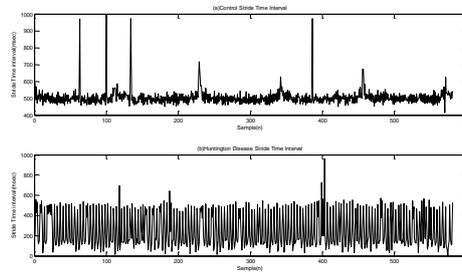


Figure 2. An example of stride time interval (a) Control stride time interval and (b) Huntington stride time interval.

2.2 Methods

As shown in Figure 2, it is obvious that the waveform is two-tier and their statistical characteristics are distinguishing features. Therefore, we decided to use first-order fractal dimensions and statistical properties to distinguish the two classes. We will describe these features below.

Katz fractal dimension

One method of calculating the fractal dimension was introduced by Katz in 1988 [9]. In this method, FD is defined as follows:

$$FD = \frac{\ln(N - 1)}{\ln(N - 1) + \ln\left(\frac{d}{L}\right)} \quad (1)$$

Where N is the total number of data points in the data time series for analysis, L is the total length of the data segment and d is the diameter of the data.

Sevcik fractal dimension

In the Sevcik method [10], the data are first normalized by scaling the time axis and coordinates (EEG signal) of the data space to fit in a single square:

$$i' = i/N, s'(i') = (s(i) - s_{min}) / (s_{max} - s_{min}) \quad (2)$$

Where s(i) and s'(i') are the original and normalized EEG signals from the ith data point, s_{max} and s_{min} are the maximum and minimum signal values and i = 1, 2, ..., N. i' is the serial number of the data points and i' is a normal. FD was then calculated as:

$$FD = 1 + \frac{\ln(L)}{\ln(2(N-1))} \quad (3)$$

where L is the total length of the data section in the normalized coordinate system.

Higuchi fractal dimension

Higuchi method was based on different measurements of signal length [11]. For a specific time series of data for analysis, k new time series are constructed as follows:

$$s_m^k = \left\{ s(m), s(m+k), s(m+2k), \dots, s\left(m + \text{int}\left(\frac{N-m}{k}\right)k\right) \right\}, m = 1, 2, \dots, k \quad (4)$$

Where m is the initial data point. k is the distance to select the next data points. And the function $\text{int}(x)$ is to take the integral part of the number x . For each new time series, its average length $L_m(k)$ is defined as follows:

$$L_m(k) = \frac{\sum_{i=1}^{\text{int}\left(\frac{N-m}{k}\right)} |s(m+ik) - s(m+(i-1)k)| \cdot \frac{(N-1)}{\text{int}\left(\frac{N-m}{k}\right) \cdot k}}{k} \quad (5)$$

Where $(N-1) / (\text{int}((N-m)/k) \cdot k)$ is a normalizing factor. The mean length of the original time series was calculated as the mean $L_m(k)$:

$$L(k) = \frac{1}{k} \sum_{m=1}^k L_m(k) \quad (6)$$

Since $L(k)$ for the fractal time series is proportional to k^{-FD} , the FD signal in this study as the slope of the curve $\ln(L(k))$ vs. $\ln(1/k)$ using the least squares best method Linear.

Mean and Standard Deviation

For statistical evaluation, we used the mean and standard deviation of step time interval. Mean and standard deviation are calculated with Equations 8 and 9.

$$\mu = \frac{\sum_{i=1}^N x(i)}{N} \quad (7)$$

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x(i) - \mu)^2} \quad (8)$$

$x(i)$ which is a time series instance, N is the mean value in terms of sample number, μ is the standard time series deviation σ .

3. Results

Using the fractal dimension of Higuchi, Sokich, and Katz, and the mean and standard deviation of the time interval of the control step and Huntington classes, we obtained 5 properties for each subject. Using these features, we decided to categorize these classes. For this purpose, we use an MLP neural network as a classifier. Our neural network has a hidden layer that contains 9 neurons. For the practice and test method, we use the K-

fold method and repeat this method 10 times, and the accuracy, sensitivity and specificity of this study are shown in Table 1.

Table 1. Values of Accuracy, Sensitivity and Specificity

	Accuracy	Sensitivity	Specificity
Value	97.22%+0.07%	94.37%	99.5%

Figure 3 shows a box diagram of Huntington's disease control features. Figure 3 (a) shows the Sevkic fractal dimension, (b) shows the Katz fractal dimension, (c) shows the Higuchi fractal dimension, (d) shows the mean value, and (e) the deviation value. Indicated the standard.

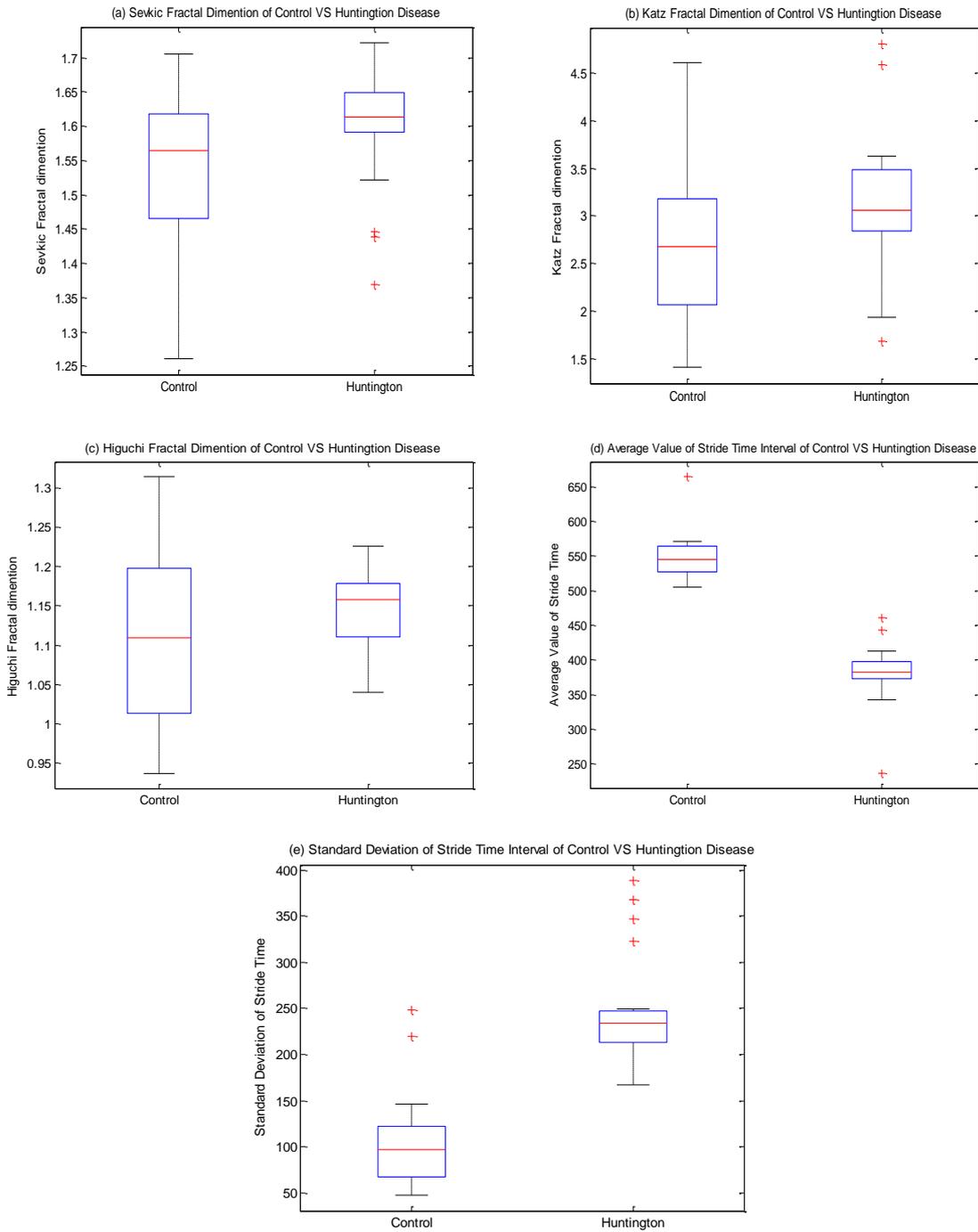


Figure 3. Box plot of features

4. Conclusion

Huntington's disease is more common in adults. In this paper, a new algorithm for classifying Huntington individuals and controlling them using step spacing is presented. The proposed algorithm had 3 steps. In the first step, we extracted the step time interval. Next, in addition to the mean and standard deviation of the standard, we extracted the

Higuchi, Sokich, and Katz fractal dimensions as a step interval feature. The main reason for choosing the fractal dimension is the difference between the form and the fraction control and the time interval of the Huntington's disease steps. According to the results, the best fractal dimension for this study was the Sevcik fractal dimension with 81.3% and the worst dimension was the Higuchi fractal dimension with 78.7% accuracy. Another comparison between the fractal dimensions is the velocity of the progress calculation. By this comparison, the Katz fractal dimension is the best and the Higuchi fractal dimension is the worst. In the last step, we used the MLP neural network with a hidden layer of 9 neurons. Compared to popular classification algorithms such as SVM and LDA, MLP shows better classification results. MLP shows a better result because in the scattered diagram space our properties show a nonlinear pattern so MLP as a nonlinear classifier shows a better result. It is recommended that you use this new algorithm for other neurodegenerative disorders such as Parkinson.

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