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Motor Signal Intelligent Processing in Huntington Disease Diagnosis

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Abstract

Movement disorder is one of the common symptoms of Huntington's disease (HD) that afflicts patients in controlling their movements. The main objective of this paper is to detect abnormal patterns of the foot during gating. The total number of 40 subjects included 16 healthy and 20 HD patients were investigated. All of the subjects were asked to gait in a 70m straight route. The time and time-frequency domain analyses have been used. The support vector machine (SVM) was performed to classify the normal and HD groups. The results showed that using a radial basis function with a combination of time and time-frequency features could better detect the abnormal patterns generated by the motor signal. The classification results for differentiating normal and HD subjects were achieved to the sensitivity and specificity of 93.46% and 91.93%, respectively. This study showed that the proposed algorithm is useful for the early diagnosis of gait pathologies. The results showed accurate performance of this method with the potentials to replace foot sensors signals as a means of classifying gait patterns.

Keywords: Motor signals; Huntington's disease; Feature selection, Classification.

1. INTRODUCTION

Huntington's disease is a chronic neurological disorder. This means that the nerve cells in the patient's brain are destroyed over time. The disease usually starts between ages 30 and 50, but can also begin at an earlier age [1-2]. It disrupts movement, behavior, speech, perception, and memory. In general, it makes the person unable to perform daily activities and causes depression, emotional problems, sleep changes, and lack of emotional control.

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Symptoms of HD develop in cognitive, motor, and mental levels. Cognitive impairment makes it difficult for the patient to learn and slows the processing of thoughts, and he cannot focus on specific works. The patient loses his flexibility and does not have the ability to start work or even start a conversation. Movement disorder can make the muscles tight, and the patient has a problem in walking and maintaining the body's balance and is almost unable to perform fast movements while the movements are abrupt, irregular, unpredictable, non-stereotyped [3-4]. The patient has difficulty in speaking, and even eye-tracking is entirely abnormal. Psychiatric disorders appear as depression, anxiety, and excessive fatigue. Insomnia and unusual oversleeping are other symptoms of this disorder [5].

The proliferation of these genes in the body results in HD because it destroys the brain's neural cells and causes a person to experience physical, mental, and functional disabilities. Identification of people who are high-risk for HD can play a significant role in reducing the severity of the symptoms and preventing the total disability in old ages [6]. The prevalence of HD varies widely across countries. In parts of Western Europe, including the region of Lake Maracaibo in Venezuela (700 per 100,000), Mauritius off the coast of South Africa (46 per 100,000), and Tasmania (17.4 per 100,000), the outbreak has been unexpected. The prevalence in most European countries is between 1.63-9.95 per 100,000 and less than 1 in 100,000 in Finland and Japan [7-8].
Electromyogram (EMG) is the electrical response of the muscle contraction. Non-invasive recording of this signal by surface electrodes can be used in many areas. One of the most critical applications of this signal is the diagnosis of neuromuscular diseases and an appropriate method for detecting the movements and conduction of various organs of the body. EMG is a common method of monitoring the nervous system activities [9].

Previous studies in the field of movement assessments used different signal processing and feature extraction methods such as Fourier Analysis (FA), wavelet transform (WT), principal component analysis (PCA), independent component analysis (ICA), and artificial neural network (ANN) [10-14].

The aim of this study was to detect HD based on time- and time-frequency domain characteristics of gait signals. To increase the efficiency of the proposed algorithm, the dimensionality reduction method is used to enhance the intelligent learning algorithm.

The rest of the paper is organized as follows. In Section 2, we describe the database, theory of the algorithms , and classification method proposed. The experimental results are shown in Section 3. A discussion of the results is provided in Section 4 , and the concluding remarks are given in Section 5.

2. MATERIALS AND METHODS

2.1. Database

We take the gait data set from gait dynamics in the neurodegenerative disease database (http://www.physionet.org/physiobank/database/gaitndd/). The data includes 16 healthy subjects and 20 HD patients. All subjects were instructed to walk at their normal pace along a 77-m hallway for 5 min

[15-16]. The sensors placed in the shoes of the subjects recorded changes in force applied to the ground during walking, at a sampling rate of 300 Hz. Tables 1 presents the characteristics of subjects.

Recorded data were divided into 7-time series including the right and left stance, right and left swing and right, left stride, and double stride. Stance time is the period in which the force is applied by the foot to the sensor. The time duration that no force is applied to the sensor through the foot refers to the swing time. The sum of the stance and swing are called stride. Meanwhile, the time in which both feet meet the ground is called a double stance.

Figures 1 to 3 show the time series associated with the stride, swing, and stance of right feet in normal and HD subjects, respectively. The first few seconds of the signals are removed to eliminate the unwanted fluctuations at the beginning.

2.2. Method

Several features can be used to analyze and detect disorders in motor signals in HD patients. Previous studies, perform

Table 1. ***Characteristics of studied Healthy and HD subjects.***

No	Age	Height	Weight	Gender	Gait speed (m/s)	No	Age	Height	Weight	Gender	Gait speed (m/s)
1	42	1.86	72	Male	1.68	1	57	1.94	95	Female	1.33
2	41	1.78	58	Female	1.05	2	22	1.94	70	Male	1.47
3	66	1.75	63	Female	1.05	3	23	1.83	66	Female	1.44
4	47	1.88	64	Female	1.4	4	52	1.78	73	Female	1.54
5	36	2	85	Male	1.82	5	47	1.94	82	Female	1.54
6	41	1.83	59	Female	1.54	6	30	1.81	59	Female	1.26
7	71	2	75	Male	1.05	7	22	1.86	64	Female	1.54
8	53	1.81	56	Female	1.26	8	22	1.78	64	Female	1.33
9	54	1.8	90	Female	1.26	9	32	1.83	68	Female	1.47
10	47	1.78	102	Female	1.05	10	38	1.67	57	Female	1.4
11	33	1.97	84	Male	1.26	11	69	1.72	68	Female	0.91
12	47	1.92	75	Male	1.19	12	74	1.89	77	Male	1.26
13	40	1.72	48	Female	0.56	13	61	1.86	60	Female	1.33
14	36	1.88	97	Female	1.4	14	20	1.9	57	Female	1.33
15	34	1.94	88	Female	0.56	15	20	1.83	50	Female	1.19
16	70	1.83	93	Male	0.56	16	40	1.74	59	Female	1.33
17	29	1.78	76	Female	1.19						
18	54	1.72	53	Female	0.98						
19	59	1.78	58	Female	0.98						
20	33	1.57	45	Female	Lost						

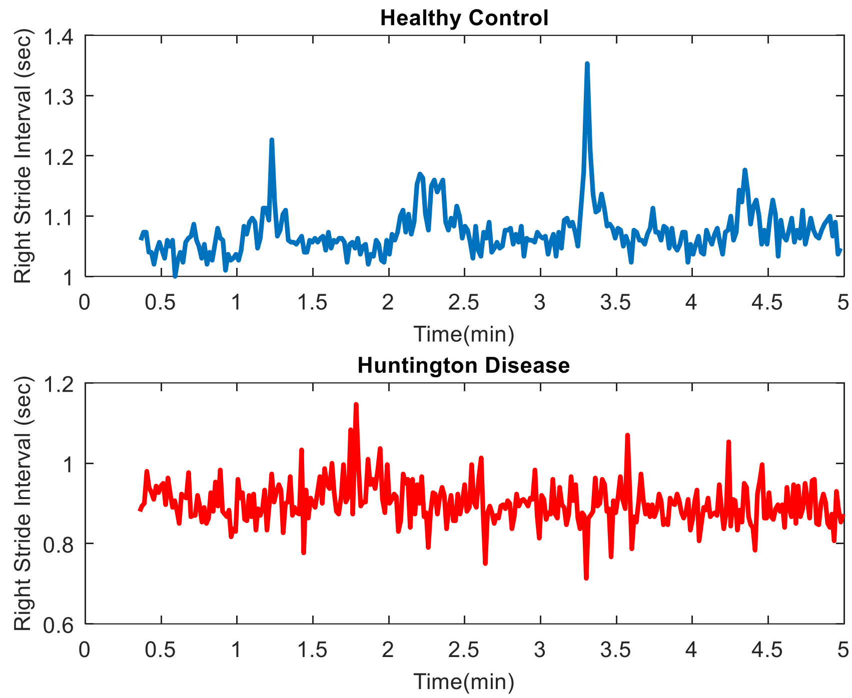

Fig. 1. Right stride time-series of the normal (top) and patient (bottom) subjects.

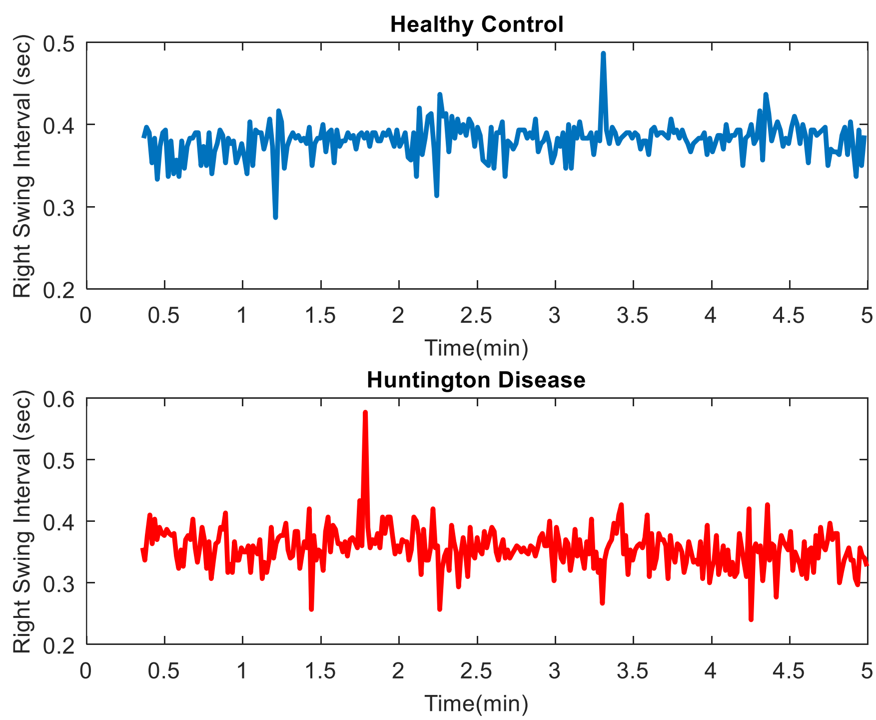

Fig. 2. Right swing time-series of the normal (top) and patient (bottom) subjects.

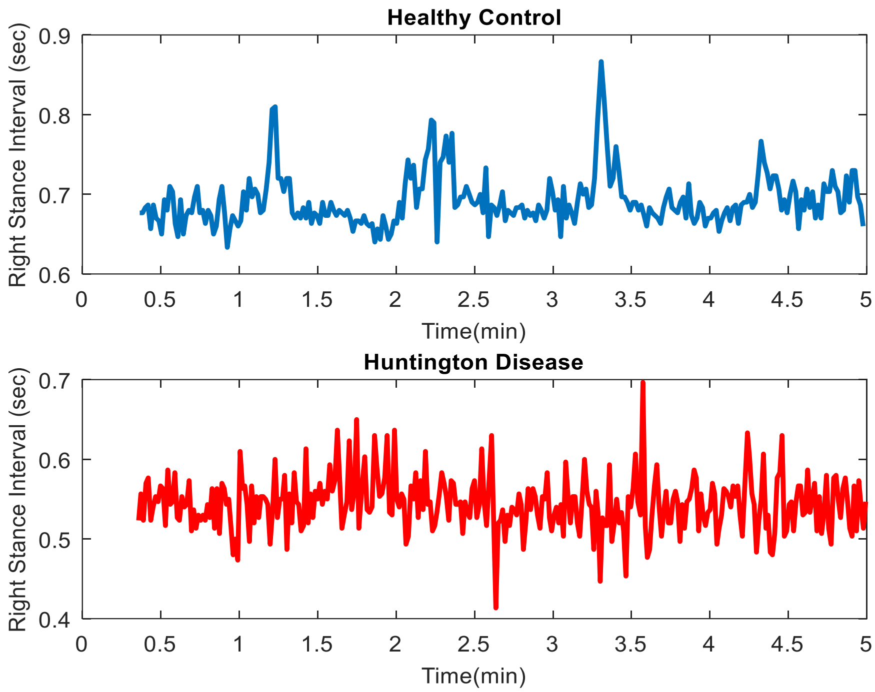

Fig. 3. Right stance time-series of the normal (top) and patient (bottom) subjects.

frequency-domain analysis to identify the changes in similar diseases to HD [17-20]. In this paper, considering the movement disorders in the patient and creating more fluctuations in their recorded signals, the time-domain and time-frequency domain features were used to classify the subjects into two groups of normal and HD. Table 2 summarized the characteristics and their formula, which were utilized for differentiating between HD and normal subjects in the current study.

2.3. Reducing the Feature Dimensions

Feature selection is one of the most important steps in the classification of normal and abnormal subjects. Among the various features extracted from the gait signal, the optimal selection of the features that might lead to the best classification results is challenging. However, removing features that have duplicate information can reduce the size of the feature vector, complexity of calculations, and speed up the system to achieve the desired response. Given that the best features are not always applicable in precise diagnosis and classification of groups, features must be specified in a way that their combination leads to desired results.

After extracting the features in the previous section from the stance, swing, and stride signals, six features were selected with 98% energy storage for the classification. These features are selected such that the ratio of dispersion between the classes to the dispersion in the classes was maximized. Finally, we have a matrix feature vector with a size of 18*36. Figure 4 shows the basic component vector in three dimensions.

Table 2. ***A summary of time and time-frequency domain features performed in the current study.***

No	Feature	Math formula
1	Maximum frequency	$MF = \mathrm{mux}(S_i)$
2	Average frequency	$AF = \frac{\sum_{i=1}^{N} f_i \times S_i}{\sum_{i=1}^{N} S_i}$
3	Total power	$\sum_{i=1}^{N} S_i$
4	Average power	$\frac{1}{N}\sum_{i=1}^{N} S_i$
5	Sum of the absolute signal amplitude	$\sum_{i=1}^{N} \lvert x_i \rvert$
6	Average absolute of the signal amplitude	$\frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$
7	Power of the signal	$\sum_{i=1}^{N} {x_i}^2$
8	Standard deviation	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (x_{i+1} - x_i)^2}$
9	Average wavelet coefficients	$\frac{1}{K}\sum_{i=1}^{K} G_i$
10	The standard deviation of wavelet coefficients	$\sqrt{\frac{1}{K-1}\sum_{i=1}^{K} (G_{i+1} - G_i)^2}$
11	Wavelet power	$\sum_{i=1}^{K} {G_i}^2$
12	Average wavelet power	$\frac{1}{K}\sum_{i=1}^{K} {G_i}^2$

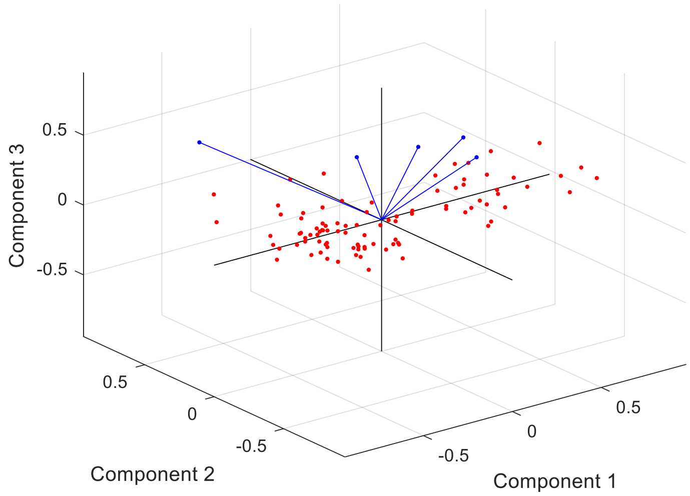

Fig.4. 3D Presentation of five main components.

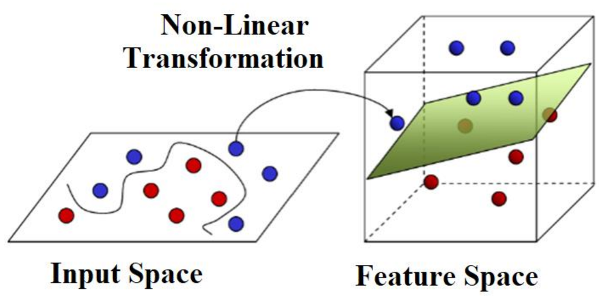

Fig. 5. Transferring data from the input to feature space.

2.4. Classification system

In this paper, the Support Vector Machine was used for the classification of two groups. This algorithm, which is a supervised and parametric learning method, transforms the data set into learning vectors so that each vector corresponds to an output value. When data is not easily separated, a linear classifier cannot be useful. Data transfer to a higher-dimensional space can result in a solution for its differentiation. Figure 5 shows an image in which linear data differentiation is not feasible in a 2D space, but using a transform, the data is transferred to a higher space, and the possibility of separating them is provided.

3. RESULTS

The wavelet transform was used to calculate the power spectrum and extract the time-frequency domain parameters. Figures 6 and 7 illustrate the power spectrum density of the right stride of the normal and patient subjects. As can be seen, the fluctuations in the power spectrum associated with the patient's stride signal are greater than healthy subjects, which motivated the researchers to work on the extracted features in this domain.

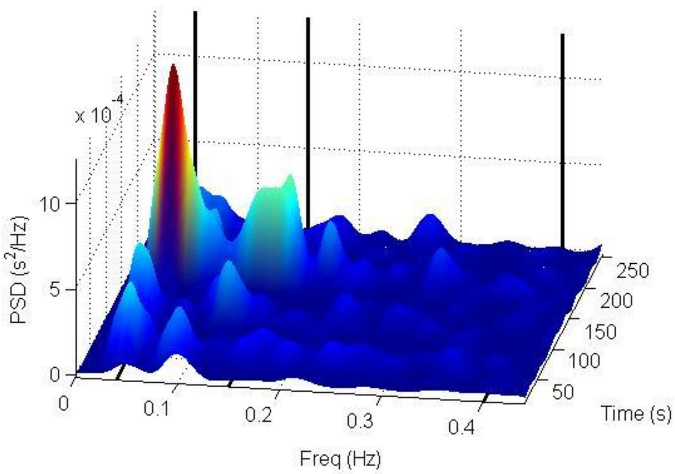

Fig. 6. Power spectral density of a healthy subject's stride signal.

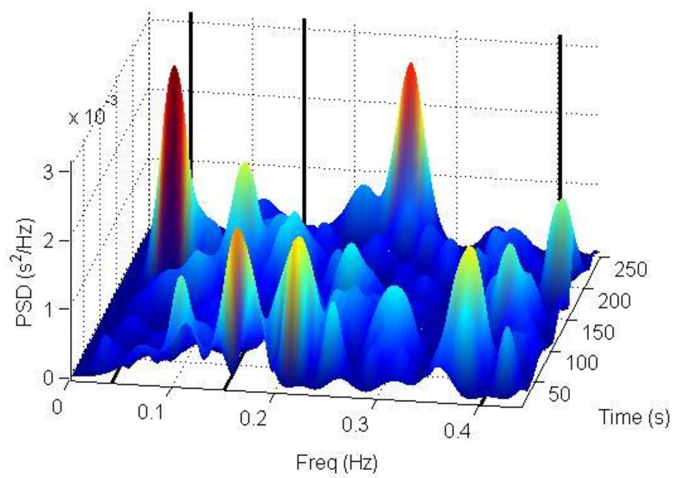

Fig. 7. Power spectral density of a sample HD patient's stride signal.

Tables 3 and 5 present the sensitivity and specificity of the SVM classifier for full and selected feature vectors with various kernels. Accordingly, when all of the features described in Table 3 are used, the average system sensitivity using radial basis and polynomial kernels were 83.23% and 82.67%, respectively. The sensitivity of classification using the selected features by the radial basis and polynomial kernels were 93.46% and 92.12%, respectively.

4. DISCUSSION

Gait dysfunction is a common problem in older people and patients with a variety of neurological disorders. Obtaining biophysical signals through pressure sensors and analyzing people's walk with mathematical algorithms has been one of the important areas of research in recent years [21]. Unfortunately, there are very few

Table 3. ***Comparison of the average sensitivity (%) of the system using different inputs and kernels.***

Input	Kernel type	
	Radial basis function	Polynomial
All features	83.23	82.67
Selected features	93.46	92.12

Table 4. ***Comparison of the specificity of the algorithm (%) using different inputs and kernels***.

Input	Kernel type	
	Radial basis function	Polynomial
All features	82.66	81.27
Selected features	93.91	92.90

databases that record such signals from patient groups that need to be studied [22].

Due to the small number of available data, it is difficult to obtain an appropriate method for analyzing them. Assessment of probable relationships, for example, the correlation between disease severity and analytical results is not possible. Most articles have shown differences between disease groups and healthy controls, but have failed to investigate relationships such as the effects of treatment, medication, or duration of disease.

Unfortunately, the automatic diagnosis methods of musculoskeletal disorders based on information extracted from the action potentials cannot provide satisfactory results for rehabilitation specialists. The weakness associated with these methods can be attributed to the inaccurate signal recording, lack of choosing the appropriate features, and weakness in the structure of the classifiers.

Enas Abdulhay et al. presented an algorithm based on machine learning using the gait analysis. Different features of gait were extracted using the peak detection and pulse duration. Average accuracy of 92.7% was obtained [23]. Sachin Shetty el. al introduced a method for Parkinson detection using statistical feature vector derived from the time-series gait data. In this study, SVM classification with Gaussian radial basis function kernel used to classify the disease. The Results of the SVM classifier showed good overall accuracy of 83.33% [24]. Marc Bachlin et al. proposed a wearable assistant for Parkinson's disease patients. In this study, to detect the Parkinson's disease used for the freezing of gait (FOG) symptoms. This algorithm detected FOG events online with a sensitivity of 73.1% and a specificity of 81.6% [25].

HD is one of the most commonly reported neuromuscular, which causes different symptoms in motor behavior over time. These specific signs and patterns of motion are more common in the patient's gait pattern. The main goal of this study is to provide an algorithm to distinguish HD patients from healthy subjects at a mild stage. We attempted to select the appropriate features to differentiate HD patients based on the motor signal instead of EMG. The results of the proposed algorithm showed that the use of SVM with radial basis kernel is more capable of classifying normal and HD patients. Moreover, the selection of optimal features extracted from motor signals improved the performance of the algorithm.

5. CONCLUSION

Automatic diagnosis of specific patterns to the HD plays a significant role in controlling the patients and increasing their quality of life. One of the important achievements of this study is the classification of EMG signal into normal and HD groups based on a simple and cost-effective method. Usually, the clinical diagnosis of HD is based on the physician's experience. Our results showed that the proposed method in this article has high efficiency in the diagnosis of HD. However, the proposed algorithm should be evaluated on a larger number of patients for better evaluations.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interest.

COMPLIANCE WITH ETHICAL STANDARDS

This article does not contain any studies with human participants or animals performed by any of the authors.

LIST OF ABBREVIATIONS

ANN: Artificial neural network; *EMG:* Electromyogram; *FA:* Fourier analysis; *FOG:* Freezing of gait; *HD:* Huntington's disease; *ICA:* Independent component analysis; *PCA:* Principal component analysis; *SVM:* Support vector machine; *WT:* Wavelet transform.

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