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Research article

# Parkinson's disease classification using gait analysis via deterministic learning

Wei Zeng[a,*], Fenglin Liu[a], Qinghui Wang[a], Ying Wang[a], Limin Ma[b], Yu Zhang[b]

[a] School of Mechanical & Electrical Engineering, Longyan University, Longyan 364012, PR China
[b] Department of Orthopaedic Surgery, Guangzhou General Hospital of Guangzhou Military Command, Guangzhou 510010, PR China

## HIGHLIGHTS

- We present a new method to classify Parkinson's disease via deterministic learning theory.
- The dynamics of gait motions can be learned by using RBF neural networks.
- The Parkinson's diseases can be classified based on the smallest error principle.
- The discriminability provided by the vertical ground reaction force feature is strong.
- We show good classify performance on the well-known PhysioBank database.

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## ABSTRACT

Gait analysis plays an important role in maintaining the well-being of human mobility and health care, and is a valuable tool for obtaining quantitative information on motor deficits in Parkinson's disease (PD). In this paper, we propose a method to classify (diagnose) patients with PD and healthy control subjects using gait analysis via deterministic learning theory. The classification approach consists of two phases: a training phase and a classification phase. In the training phase, gait characteristics represented by the gait dynamics are derived from the vertical ground reaction forces under the usual and self-selected paces of the subjects. The gait dynamics underlying gait patterns of healthy controls and PD patients are locally accurately approximated by radial basis function (RBF) neural networks. The obtained knowledge of approximated gait dynamics is stored in constant RBF networks. The gait patterns of healthy controls and PD patients constitute a training set. In the classification phase, a bank of dynamical estimators is constructed for all the training gait patterns. Prior knowledge of gait dynamics represented by the constant RBF networks is embedded in the estimators. By comparing the set of estimators with a test gait pattern of a certain PD patient to be classified (diagnosed), a set of classification errors are generated. The average $L_1$ norms of the errors are taken as the classification measure between the dynamics of the training gait patterns and the dynamics of the test PD gait pattern according to the smallest error principle. When the gait patterns of 93 PD patients and 73 healthy controls are classified with five-fold cross-validation method, the accuracy, sensitivity and specificity of the results are 96.39%, 96.77% and 95.89%, respectively. Based on the results, it may be claimed that the features and the classifiers used in the present study could effectively separate the gait patterns between the groups of PD patients and healthy controls.



## 1. Introduction

Parkinson's disease (PD) is a typical disorder of the basal ganglia. It is associated with characteristic changes in resting tremor, muscle rigidity, bradykinesia, and postural instability; all of which increase the risk of gait instability [1]. The primary symptoms are due to decreased stimulation of the motor cortex by the basal ganglia.

Exact diagnosis of PD may be delayed in early stages, as structural neuroimaging methods do not provide characteristic features to allow the diagnosis of PD [2]. Since two cardinal PD symptoms (postural instability and rigidity) alter the gait patterns, gait analysis may help PD diagnosis (classification). Gait information has been widely used for the movement studies in healthy controls

* Corresponding author.
*E-mail address:* zw0597@126.com (W. Zeng).

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and also in subjects with PD. Analysis of gait parameters is very useful for a better understanding of the mechanisms of movement disorders, and also has the high potential in presenting automatic non-invasive method based on gait characteristics for the diagnosis of PD [3]. To classify PD patients and healthy control subjects, kinetic, spatio-temporal, power spectral, and fractal parameters of the gait, have been used in previous studies [4–15]. Different methods have tried to analyze the PD quantitatively: some studies wanted to analyze the PD symptoms quantitatively, some studies tried to model the PD, and some of them studied the disease with dynamical systems view.

Jeon et al. [16] studied the classification of PD patients and healthy controls using spatial-temporal image of plantar pressure. They also used support vector machine classifier by kernel function. Mariani et al. [17] studied an innovative technology based on on-shoe wearable sensors and processing algorithm to provide outcome measures, which included turning, swing width, path length, and their intercycle variability. They were used to characterize PD motor symptoms and classify between PD patients and healthy controls. Wu and Krishnan [18] studied the nonparametric Parzen-window method to estimate the probability density functions of stride interval and its two subphases. Their study demonstrated that the gait variability, in terms of statistical parameters of stride interval, would be increased in PD. The least squares support vector machine with polynomial kernels was able to provide a classification accurate rate of 90.32% between 16 PD patients and 13 healthy controls.

Besides the analysis of PD symptoms (e.g., gait), modeling approaches have also been used for PD evaluation and some of them presented good findings or hypotheses. In 2005, Haeri et al. [19] focused on basal ganglia structure and presented a mathematical model for tremor. While being a simple model and accepting some assumptions as considering the tremor to be simple sinusoidal signals, the role of drugs and deep brain stimulation treatments were simulated fairly suitable and clinically plausible. Pascolo et al. [20] evaluated time series of posture variations in normal and PD patients, four cases in each group. They showed that normal and PD patients had some differences in chaotic features. They have emphasized that more studies were needed to show these chaotic differences. In 2012, Sarbaz et al. [21] used the sine circle map relation for simulating the basal ganglia structure. This relation could explain the complex behaviors and the complex structure of the basal ganglia. There was a significant difference between the model parameter of normal and PD patients which could be used to distinguish the two groups.

Our primary interest in this paper is to investigate if the ground reaction force (GRF), which is the kinetic parameter of gait, can be used to distinguish between PD patients and healthy controls. Measurements on these two groups have shown that: (a) the GRF displays a characteristic pattern due to cardiac activity; (b) the GRF contains valuable quantitative data of gait characteristics, reflecting effects of internal and external forces [22–24]. It has been used for evaluation of human movement [22,25], diagnosis [26], and pattern recognition [27]. Lee and Lim [28] extracted wavelet-based features from the vertical GRFs using the gait characteristics of idiopathic PD patients. Then, they used the features as inputs of the neural network with weighted fuzzy membership functions to classify both idiopathic PD patients and healthy controls. Daliri [29] used the vertical GRFs computed by using 8 sensors placed underneath of each foot. The short-time Fourier transform was used to extract several features from the spectral of time series forces and histograms of these features were then formed. The distances between histograms were computed using the chi-square distance and a kernel was created from these distances. The support vector machines were used finally to classify PD patients and healthy controls. Inspired by the above studies, we attempt the classification of PD based on the difference of gait dynamics represented by the vertical GRFs between PD patients and healthy controls.

The aim of this study is to develop a new method using gait analysis to classify (diagnose) patients with PD and healthy control subjects via deterministic learning theory. The classification approach consists of two phases: a training phase and a classification phase. In the training phase, gait characteristics represented by gait dynamics are derived from the vertical GRFs under the usual, self-selected paces of the subjects. Gait dynamics underlying gait patterns of healthy controls and PD patients are locally accurately approximated by radial basis function (RBF) neural network (NN). The obtained knowledge of approximated gait dynamics is stored in constant RBF networks. The gait patterns of healthy controls and PD patients constitute a training set. In the classification phase, a bank of dynamical estimators is constructed for all the training gait patterns. Prior knowledge of gait dynamics represented by the constant RBF networks is embedded in the estimators. By comparing the set of estimators with a test gait pattern of a certain PD patient to be classified (diagnosed), a set of classification errors are generated. The average $L_1$ norms of the errors are taken as the classification measure between the dynamics of the training gait patterns and the dynamics of the test PD gait pattern according to the smallest error principle. The proposed method can effectively separate the gait patterns between the groups of healthy controls and PD patients.

The rest of the paper is organized as follows. Section 2 introduces preliminary knowledge about deterministic learning theory and problem formulation. Section 3 describes the proposed method. This includes the data description, feature extraction and selection, learning and classification mechanisms. Section 4 presents experimental results. Section 6 contains the conclusions.

## 2. Preliminaries and problem formulation

### 2.1. Deterministic learning theory

In deterministic learning theory, identification of system dynamics of general nonlinear systems is achieved according to the following elements: (i) employment of localized RBF networks; (ii) satisfaction of a partial persistence of excitation (PE) condition; (iii) exponential stability of the adaptive system along the periodic or recurrent orbit; (iv) locally-accurate NN approximation of the unknown system dynamics [30,31].

The RBF networks can be described by $f_{nn}(Z)=\sum_{i=1}^{N} w_i s_i(Z)=W^T S(Z)$, where $Z\in\Omega_Z\subset R^p$ is the input vector, $W=[w_1,\ldots,w_N]^T\in R^N$ is the weight vector, $N$ is the NN node number, and $S(Z)=[s_1(\|Z-\mu_1\|),\ \ldots,\ s_N(\|Z-\mu_N\|)]^T$, with $s_i(\cdot)$ being a radial basis function, and $\mu_i (i=1,\ \ldots,\ N)$ being distinct points in state space. The Gaussian function $s_i(\|Z-\mu_i\|)=\exp[(-(Z-\mu_i)^T(Z-\mu_i))/\eta_i^2]$ is one of the most commonly used radial basis functions, where $\mu_i=[\mu_{i1},\ \mu_{i2},\ \ldots,\ \mu_{iN}]^T$ is the center of the receptive field and $\eta_i$ is the width of the receptive field. The Gaussian function belongs to the class of localized radial basis functions in the sense that $s_i(\|Z-\mu_i\|)\rightarrow 0$ as $\|Z\|\rightarrow\infty$.

It has been shown in [32] that for any continuous function $f(Z):\Omega_Z\rightarrow R$ where $\Omega_Z\subset R^p$ is a compact set, and for the NN approximator, where the node number $N$ is sufficiently large, there exists an ideal constant weight vector $W^*$, such that for each $\epsilon^*>0$, $f(Z)=W^{*T}S(Z)+\epsilon(Z)$, $\forall Z\in\Omega_Z$, where $|\epsilon(Z)<\epsilon^*|$ is the approximation error. Moreover, for any bounded trajectory $Z_\zeta(t)$ within the compact set $\Omega_Z$, $f(Z)$ can be approximated by using a limited number of neurons located in a local region along the trajectory: $f(Z)=W_\zeta^{*T}S_\zeta(Z)+\epsilon_\zeta$, where $S_\zeta(Z)=[s_{j_1}(Z),\ldots,s_{j_\zeta}(Z)]^T\in R^{N_\zeta}$, with $N_\zeta<N$, $|s_{j_i}|>\iota (j_i=j_1,\ldots,j_\zeta)$, $\iota>0$ is a small positive constant, $W_{\zeta *}=$