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Classification of neurodegenerative diseases using gait dynamics via deterministic learning

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ABSTRACT

Neurodegenerative diseases (NDDs), such as Parkinson's disease (PD), Huntington's disease (HD) and amyotrophic lateral sclerosis (ALS), create serious gait abnormalities. They lead to altered gait rhythm and gait dynamics which can be reflected by a time series of stride-to-stride measures of footfall contact times. The temporal fluctuations in gait dynamics provide us with a non-invasive technique to evaluate the effects of neurological impairments on gait and its variations with diseases. In this paper, we present a new method using gait dynamics to classify (diagnose) NDDs via deterministic learning theory. The classification approach consists of two phases: a training phase and a classification phase. In the training phase, gait features representing gait dynamics are derived from the time series of swing intervals and stance intervals of the left and right feet. Gait dynamics underlying gait patterns of healthy controls and NDDs subjects are locally accurately approximated by radial basis function (RBF) neural networks. The obtained knowledge of approximated gait dynamics is stored in constant RBF networks. Gait patterns of healthy controls and NDDs subjects 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 NDDs gait pattern to be classified, a set of test 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 NDDs gait pattern according to the smallest error principle. Finally, experiments are carried out to demonstrate that the proposed method can effectively separate the gait patterns between the groups of healthy controls and neurodegenerative patients.

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1. Introduction

Neurodegenerative diseases (NDDs), including Parkinson's disease (PD), Huntington's disease (HD), and amyotrophic lateral sclerosis (ALS), produce changes in altered neuromuscular control. Since flexion and extension motions of two lower limbs are regulated by the central nervous system, the gait of a patient with a neurodegenerative disorder would become abnormal due to deterioration of motor neurons. PD and HD are typical disorders of the basal ganglia and are associated with

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characteristic changes in gait rhythm [4]. ALS is a disorder primarily affecting the motoneurons of the cerebral cortex, brain stem, and spinal cord [2]. Because the neurons of the basal ganglia likely play an important role in regulating muscular motor control such as balance and sequencing of movements, it is reasonable to expect that the stride-to-stride dynamics, as well as the gait cycle duration, are affected by these NDDs. Gait information has been widely used for the movement studies in healthy controls and also in subjects with different types of diseases. Analysis of temporal 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 dynamics for the classification of NDDs [2].

Gait dynamics are regulated by a complex nervous system. It is believed that the regulatory feedback loops of a physiologic system need to operate across multiple spatial and temporal scales to be able to adapt to an ever changing environment [30]. Thus, the time series of stride, stance or swing intervals are likely to exhibit fluctuations across multiple spatial and temporal scales [15]. In recent related studies, computer-aided tools have been utilized to measure the gait interval parameters in healthy adults, and also to describe the distinct characteristics of the gait in NDDs [8,9,16,19,22,20,24,27–29,32,37,40,43,31]. Aziz and Arif [2] converted the stride time series into a kind of symbol sequence, then applied a threshold dependent symbolic entropy method in the analysis of gait complexity. They observed that the normalized corrected Shannon entropy of the symbolic stride sequences is much lower in ALS at different short thresholds. Scafetta et al. [29] used the supercentral pattern generator (SCPG) model to simulate human gait dynamics, and also discussed the stochastic and fractal properties of the gait in PD, HD and ALS. Wu and Shi [41] proposed a statistical analysis method for the classification of gait cadence in subjects with ALS and healthy controls. In their approach, the probability density functions of gait cadence were estimated using Parzen-window method and then the Kullback–Leibler divergence was derived. With this method it was able to classify the stride patterns of the ALS and the control subjects with the accuracy rate of 82.8%. In their another similar study [39], it was hypothesized that the swing interval turns count (SWITC) of the ALS patients might be different from that of healthy subjects. The ALS gait patterns, characterized by the SWITC parameter and the known ASI feature, could be distinguished from the gait patterns of healthy subjects through the linear and nonlinear classifiers. Using the SWITC parameter and the average stride interval could reach to the classification rate of 89.66% for the gaits in subjects with ALS and gaits in healthy control subjects. Daliri [7] presented an approach for the diagnosis of NDDs based on gait dynamics. The proposed method used information from a time series of stride intervals, swing intervals, stance intervals and double support intervals of stride-to-stride measures. The support vector machines using different kernels were examined for the diagnosis. Based on the findings in [3], a reasonable approach to investigate the effects of neurological impairments on patients' ability to mediate the locomotion of two lower limbs was proposed. It compared the left and right stance-interval series in terms of their regularities at multi-resolution levels. Liao et al. [23] investigated gait asymmetry in NDDs using the multi-resolution entropy analysis of stance time fluctuations. Their results showed that gait symmetry is significantly disturbed in subjects with PD, HD, and ALS, and the degree of disturbance is more prominent in the subjects with ALS. A number of scientists showed that NDDs patients present altered fractal dynamics of gait characterized by reduced stride-interval correlations, that is, the walking of these individuals becomes more random [30,18,21]. The randomness increases with the severity of the neurodegenerative impairment.

Our primary interest in this paper is to investigate modeling of gait dynamics using the time series of the left and right feet. Specifically, we would like to know whether the three types of neurological disease (PD, HD and ALS) would impair the patient's ability to regulate the locomotion of two feet and whether the difference of gait dynamics is related to the particular type of disease that the patient has. Nevertheless, research on the temporal variability of gait dynamics, such as step to step, is limited. It has been postulated that the ability to maintain a steady gait (i.e. low stride-to-stride variability of gait cycle timing and its sub-phases) would be diminished in NDDs [17]. Irregular timing of steps in NDDs suggests a disturbance of rhythmic locomotor activity generation and gait dynamics [11]. The classification (diagnosis) of NDDs based on the difference of gait dynamics between NDDs and healthy controls is what we want to attempt.

In this paper, we present a new method using gait dynamics for the classification of NDDs via deterministic learning theory. The time series of swing and stance intervals of the left and right feet are used to model gait dynamics of NDDs and healthy control subjects according to the SCPG model. Gait dynamics underlying gait patterns of healthy controls and NDDs subjects 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 NDDs subjects 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 NDDs gait pattern to be classified, a set of test 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 NDDs gait pattern to be classified according to the smallest error principle. The proposed method can effectively separate the gait patterns between the groups of healthy controls and neurodegenerative patients. Compared with other recently reported results in [41,7,10], our method achieves superior classification performance.

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 5 gives some discussions and conclusions.

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