Knowledge-Based Systems 000 (2018) 1–7

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Dual channel LSTM based multi-feature extraction in gait for diagnosis of Neurodegenerative diseases

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ARTICLE INFO

Article history:
Received 9 August 2017
Revised 29 December 2017
Accepted 2 January 2018
Available online xxx

Keywords:
Neurodegenerative diseases
Diagnosis
Gait disorders
Time series
Force series
Dual channel LSTM

ABSTRACT

The performance of gait disturbances differ in various Neurodegenerative diseases (NDs), which is an important basis for the diagnosis of NDs. In the diagnosis, doctors can judge disease state by observing patients' gait features without quantification, such a subjective diagnosis has been seen as a problem because diagnostic results may differ among doctors. Moreover, there are some irresistible factors such as fatigue may effects diagnostic procedure. To make use of these observations, we build an automatic deep model based on Long Short-Term Memory (LSTM) for the gait recognition problem. In our model, a dual channel LSTM model is designed to combine time series and force series recorded from NDs patients for whole gait understanding. Experimental results demonstrate that our proposed model improves gait recognition performance compared to baseline methods. We believe the quantitative evaluation provided by our method will assist clinical diagnosis of Neurodegenerative diseases.

1. Introduction

Neurodegenerative diseases(NDs), including Parkinson's disease (PD), Huntingtons disease (HD), and amyotrophic lateral sclerosis (ALS), produce lesions in the central nervous system that controls the motions of two lower limbs causing gait disorders. Studies assert that every individual has unique gait pattern [1] indicating that gait disorder is recognized as a contributing diagnostic criterion for NDs.

Additionally, gait performance varies among the three diseases. HD is an dominant genetic disease with nervous system gradually degenerated resulting in abnormal body movements, which may present as involuntary movements, walking and balance disorders, dance like movements, twisting, rolling, and unstable gait in middle stage [2]. Gait disturbance occurs in PD patients' early stage, such as festinating gait, short gait and freezing gait may make PD diagnosis easier [3]. The clinical features of ALS are indicative of the loss of neurons at all levels of the motor system - from the cortex to the anterior horn of the spinal cord. Physical signs of this disorder thus encompass both upper motor neuron and lower motor neuron findings; this causes the movement disorder of the limbs, for example, scissors gait and spastic gait [4].

By employing these motor symptoms, we are committed to optimizing the existing disease diagnosis system which is one of the more labor-intensive tasks in medical procedure. Despite advances in medical care, gait disturbances are known to worsen as the disease progresses, contributing to loss of independence, falls, and poor quality of life. Moreover, gait disorder based diagnosis can not provide quantitative data of diseases leading to a subjective and inefficient diagnosis process, besides, general health care systems seem not always maintain accurate and rapid diagnosis. Machine learning methods have gained popularity as they offer an objective approach to identifying or differentiating subgroups of individuals with movement disorders and quantifying outcomes of gait classification in low cost. In many cases, these methods can provide more accurate diagnosis than experienced nerve physicians so that it facilitates auxiliary diagnosis.

Recently, machine learning technologies have been effectively applied to study the gait variability in neurological diseases including the kernel Fisher discriminant (KFD), the naive Bayesian approach (NB), support vector machine (SVM) and nearest neighbor (NN) [5–8], neural networks [9,10]. However, these researches are not specifically designed to cope with temporal data, whereas the gait recorded by devices (cameras, force sensors) contains important temporal information which is significant for NDs diagnosis.

Long Short-Term Memory (LSTM) has done a good job on this issue in various fields including action recognition and gait recognition owing to the ability of processing and forecasting the time series with very long interval and delay [11–17]. Although these

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https://doi.org/10.1016/j.knosys.2018.01.004
0950-7051/© 2018 Published by Elsevier B.V.

works can effectively extract the single gait feature, it is insufficient for representing the details of gait changes. We propose a dual channel LSTM model to fuse two gait features including time series and force series to learn gait pattern of the patient. By experimenting on a public NDs gait data set, our method is testified to outperform other popular algorithms in solving this problem.

In addition, the two types of gait data were measured by a footswitch system simultaneously that provides accurate estimates of the start and end of stance phase for sequential steps based on a commercially available transducer and can be readily reproduced for use in a laboratory setting. Specifically, it contained two 1.5 in^2 force sensitive resistors and a 390Ω measuring resistor, which can obtain the stride time intervals according to the variation tendency of force changing in gait. In order to comprehensively capture the gait changes in time and space, we combine these two features to obtain better diagnostic results [18].

The rest of this paper is organized as follows. Section 2 explores the related work. Section 3 introduces the proposed dual channel LSTM network. Section 4 describes the used public data set and provides our experimental results, and Section 5 is a discussion for NDs diagnosis. Section 6 concludes the paper.

2. Related work

It is generally known that the medical institutions produce a large number of data, different features are extracted from these data, which can help doctors and patients understand the state of illness and select the proper treatment. This section introduces the related work for NDs diagnosis by using data with different features, such as skeleton feature, time feature, and force feature.

Skeleton feature is an influential reference of gait recognition, which eliminates some interference characteristics and retains only the joint point coordinate of human bones to identify gait difference. Torres et al. presented an approach of recording the posture of PD with a Kinect sensor, which can capture the changes of joint points in order to assist physicians in PD diagnosis [19]. Galna et al. established a system to measure clinically relevant movements in people with PD using skeleton data, which calculated temporal and spatial features of skeleton joints [20]. Oskarsson et al. proposed a method to determine the spectrum of 3-dimensional reachable workspace encountered in a cross-sectional cohort of individuals with ALS applying skeleton data aiming to assess the difference between healthy controls and ALS patients [21].

Gait is a time-dependent process, in which the time features of lower limb movements are also essential for gait recognition. Sarbaz et al. designed a feed-forward artificial perceptron neural network with a hidden layer as the classifier that took frequency features extracted from time intervals with a power spectrum as the input [22]. Moreover, Zeng et al. demonstrated that the proposed Radial Basis Function (RBF) neural networks model and deterministic learning fusion method can effectively separate the gait time series between the groups of healthy controls and Neurodegenerative patients (ALS, HD and PD) [9]. In addition, an artificial neural network were constructed to model healthy behavior and train gait time interval series data of patients with HD [10].

Another feature obtained by force sensors (such as force-sensitive resistors with the output roughly proportional to the force under the foot) can represent more subtle changes in lower limb movements. Manap et al. proposed the feed-forward multilayer perceptron neural network to identify PD patients from normal people with gait patterns extracted from Ground Reaction Force (GRF, in Newton) recordings [23]. Jane et al. built a Q-backpropagated time delay neural network in predicting PD severity of gait disorders using GRF [24].

Based on these temporal data in gait, finer pattern of dynamic gait details can be effectively distinguished by LSTM. We proposed a dual channel LSTM model that combining two types of features including time data and force data to model the gait dynamics of patients in NDs, which can improve the diagnostic process for objectively analyzing the changes in motor behaviors. Our experiment demonstrates that using fusion feature is more effective than that of single feature.

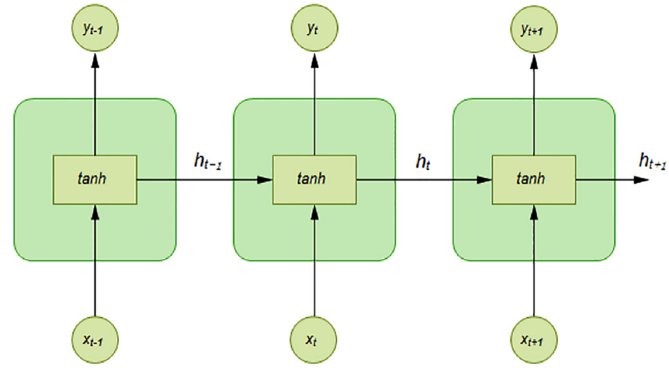

Fig. 1. A typical RNN model. Every RNN module represents a RNN cell at a time, there is an activation function "*tanh*" in it, and each module has two inputs and two outputs.

3. Methods

3.1. Introduction to RNN and LSTM

To be self-explanatory, the basic theory of RNN and LSTM will be briefly introduced before describing the structure of our proposed dual channel LSTM model in NDs classification.

RNN is a special artificial neural network where connections between units form a directed cycle, which can exhibit dynamic timing behavior. Unlike the feed-forward neural networks, the internal memory cell in RNN makes it naturally adept in handling sequential data such as connected handwriting recognition, speech recognition, and activity recognition. The RNN is a chainlike structure comprised of repeating modules that allows for information retention by combining previous states with current input [25]. This repetitive module has a simple formation ("*tanh*" function) in a basic RNN. For a given input series x_t $(t = 1, 2 \ldots, T)$, the hidden state of a recurrent module h_t is calculated using Eq. (1). The output of the module y_t is calculated as in Eq. (2). Fig. 1 shows a typical structure of RNN with 3 modules.

$$h_t = tanh(W_{xh}x_t + W_{hh}h_{t-1} + b_h) \tag{1}$$

$$y_t = softmax(W_{ho}h_t + b_o) \tag{2}$$

where W_{xh}, W_{hh}, W_{ho} indicate the connection weights from the input x to the hidden state h, the hidden state h to itself and the hidden state to the output y respectively. b_h and b_o are bias vectors, *tanh* and *softmax* are the activation functions in the hidden layer and the output layer.

However, the memory ability of RNN is weak for long time steps because of its limited function, to solve this problem, LSTM has complicated dynamics that allow it to easily memorize information for an extended number of timesteps, which has similar repetitive module to RNN and can learn long-term dependency information from the input data [26]. The internal organization of repetitive module in LSTM has four interactive operations (3 *sigmoid* and 1 *tanh*), which enables it by extracting valid information from dynamic data.

There are three gates (input, forget and output) in the basic cell of LSTM, each gate has a sigmoid activation function and a pointwise multiplication operation. We choose a variant of LSTM called

Please cite this article as: A. Zhao et al., Dual channel LSTM based multi-feature extraction in gait for diagnosis of Neurodegenerative diseases, Knowledge-Based Systems (2018), https://doi.org/10.1016/j.knosys.2018.01.004