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A Q-back propagated time delay neural network for diagnosing severity of gait disturbances in Parkinson's disease

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ABSTRACT

Parkinson's disease (PD) is a movement disorder that affects the patient's nervous system and health-care applications mostly uses wearable sensors to collect these data. Since these sensors generate time stamped data, analyzing gait disturbances in PD becomes challenging task. The objective of this paper is to develop an effective clinical decision-making system (CDMS) that aids the physician in diagnosing the severity of gait disturbances in PD affected patients. This paper presents a Q-back propagated time-delay neural network (Q-BTDNN) classifier that builds a temporal classification model, which performs the task of classification and prediction in CDMS. The proposed Q-learning induced Back-propagation (Q-BP) training algorithm trains the Q-BTDNN by generating a reinforced error signal. The network's weights are adjusted through back-propagating the generated error signal. For experimentation, the proposed work uses a PD gait database, which contains gait measures collected through wearable sensors from three different PD research studies. The experimental result proves the efficiency of Q-BP in terms of its improved classification accuracy of 91.49%, 92.19% and 90.91% with three datasets accordingly compared to other neural network training algorithms.

1. Introduction

Parkinson's disease (PD) affects the nervous system of the patients by destroying neurons in the brain that produce a chemical named dopamine. The dopamine is responsible for sending messages to the brain for movement co-ordination [1–3]. Thus, most of the PD affected patient's exhibit movement disorders resulting in the postural instability or walking disturbances [1,2]. The symptoms of PD include muscle stiffness, tremors, and changes in speech and gait [2]. Many research studies provide detailed investigations about the PD symptoms [3]. In general, a gait cycle also referred as stride contains one stance phase and one swing phase [1,2]. The stance phase represents the period at which the foot strikes on the ground. The swing phase represents the period at which the same foot lifts up the floor. A normal person's walking constitutes repetition of this gait cycle and a normal human being approximately takes 60% of stance phase and 40% of swing phase [4]. PD patients often show disturbances and variations in this gait cycle. This work analyses the gait disturbances to identify its severity in PD.

In [5–8] the authors have presented an experimental study that examines the associations between the walking speed and variations in the gait. The authors have observed that for PD patients, there is a decrease in the stride length and average swing time and an increase in the stride and swing time variations. The impact of PD in terms of movement disabilities is measured using several rating scales namely Unified Parkinson Disease (UPDRS), Hoehn and Yahr Scale, modified UPDRS [9–11]. In [12] the authors have evaluated the severity level of PD by characterizing the leg swiftness task. The authors have investigated an association between the angular amplitude and speed of thigh motion with UPDRS scores.

Though, there are several studies done to analyze the movement disorders in PD patients there are still many challenging areas of research in this domain due to the time stamped nature of PD data recorded through most of the wearable sensors.

1.1. Outline of the paper

This paper aims in developing a clinical decision-making system (CDMS) that uses an effective classification model for diagnosing the severity of gait disturbances in PD. This work presents a Q-back propagated time delay neural network (Q-BTDNN)

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classifier for building a classification model. Q-BTDNN is a dynamic feed forward time-delay neural network (TDNN) in which the learning is done using the proposed Q-learning induced back-propagation (Q-BP) technique. The proposed work is experimented with time stamped gait database acquired through wearable sensors. The experimental result, prove the effectiveness of the presented classifier in terms of its improved classification accuracy and reduced error rates.

2. Related works

In this section, few existing research work related to this paper is reviewed. Cole et al. [15] have presented dynamic machine-learning algorithms for monitoring the tremor severity and dyskinesia by analyzing signals collected from PD patients wearing small numbers of hybrid sensors. The authors have designed dynamic algorithms in pattern classification, neural networks, support vector machines and Hidden Markov Model (HMM). The experimental data were collected from eight PD patients and four healthy individuals through wearable sensors by allowing them to do unplanned and unrestricted daily living activities. The experimental results show that the performance of all the presented dynamic algorithms is equally effective in reducing the error rates.

Wangr and Jiang [17] have presented an incremental learning classification model based on fuzzy clustering algorithm and probabilistic neural networks for sensor-based human activity recognition. The presented classifier has the ability to adapt and incrementally learn from the training data. The system effectively performs classification with incremental data and proves its efficiency in terms of its learning ability and accuracy. Mazilu et al. [16] have investigated the performance of feature learning process for detecting freezing of gait (FOG) in PD patients. Three features namely statistical features, time-domain and unsupervised based on principal components analysis were considered. The experiments were conducted with acceleration data acquired from ankle of patients suffering with FOG. The experimental results prove that the statistical and time-domain features outperform the unsupervised feature extraction process.

Michael et al. [18] have presented an evolutionary algorithm, namely sliding window genetic programming (SGP) and Artificial biochemical networks (ABN) to classify the movement characteristics of Parkinson disease patients. SGP is used to capture movement patterns within a cycle. ABN is used to capture dynamical patterns occurring during time scales. Two-thirds of the clinical recordings are placed in a training set for fitness evaluation. The other third of the data is used to evaluate the classifier. Though, both the techniques effectively classify PD patients and control patients the SGP classifier outperforms ABN. The advantage of using evolutionary algorithms is to produce patterns that human might not notice.

Ene [19] have presented an application of probabilistic neural network (PNN) for classifying healthy and PD subjects. The PNN model based on three searches namely incremental search (IS), Monte Carlo search (MCS) and hybrid search (HS) were used in the classification process. The experimental study was conducted with biomedical voice measures data for twenty-five PD patients and six normal person obtained through UCI repository. From the experimental results, it can be inferred that there is no significant differences between three searches, however; the use of hybrid heuristic approach can improve the classification results.

Little et al. [20] have presented a classification technique named Kernel based Support Vector machine to diagnose the PD by identifying dysphonia. For experimentation, the authors used sustained phonations from 23 PD patients and 8-control person. It was observed that the new dysphonia measure introduced such as pitch period frequency along with another ten measures provides improved classification accuracy, which is recommended in many telemonitoring applications. Rigas et al. [21] have presented a study to illustrate that a hidden Markov model (HMM) is well suited for identifying tremors since they mostly represents temporal dependencies. They have experimented with ten patients and thirteen control subjects daily activity accelerometer data. Djuric-Jovicic et al. [22] have presented a thresholding technique and a neural network to classify PD patients based on their walking patterns. This distinguishes the normal walk and shuffling steps. For experimentation, the data were acquired using a set of six inertial measurement units attached to the subjects' legs (i.e. thigh and shin) as well as their feet. The movements of four patients for thirty minutes were collected and used to train a neural network. The error rate of the training process obtained depends on the choice of threshold.

Das [23] has presented a comparative study about various classification methods, namely Decision Tree, Neural Networks, DMneural and Regression for diagnosing PD disease. For experimentation, the authors have used biomedical voice measurements from PD patients who are suffering from speech disorder. From the experimental results, it was observed that neural network outperforms other classifiers in terms of its classification accuracy. Ahlrichs and Lawo [3] have presented a detailed review that discusses about various techniques used in diagnosing PD based on motor symptoms from times series data. The authors have provided detail descriptions about the accuracies and error rates with respect to the experimental data they have considered. Waibel [24] has proposed a time delay neural network for identifying the temporal relationships among the acoustic–phonetic features.

Comparing to the works discussed in the literature the proposed work is different in following ways: This work proposes a reinforced Q-learning back-propagation algorithm to train the TDNN in an incremental way. During the training process, the network weights are adjusted based on the reinforced back-propagated error signal. The temporal ordering among the observed gait patterns of each subjects are considered in diagnosing the severity conditions of the gait disturbances in PD.

3. Materials and methods

This section describes the dataset and methods used in the presented temporal data mining framework.

3.1. Dataset description

For experimentation, this work uses the PD gait database [25] that contains data collected in the Unit of the Tel-Aviv Sourasky Medical Center at the Laboratory for Gait & Neurodynamics, Movement Disorders. This database consists of three PD datasets used in research studies [5–8]. Totally, this database stores 93 PD subjects and 73 control subjects. Each person involved in the study is referred as a subject. In the data acquisition, a computerized force-sensitive wearable sensor from Ultraflex Computer Dyno Graphy, Infotronic Inc. [25] measures the stride-to-stride variations and gait of a subject. The wearable sensor consists of a pair of shoes each of which contains eight sensors that is placed in the insole. The subjects were asked to wear those shoes and walk using different styles such as treadmill walking, unassisted walking on a ground level, walking on a ground level using walker, dual-task walking. The vertical ground reaction force (VGRF) from each sensor measured in newtons is recorded in the attached memory card.

These walking (gait) patterns of the PD subjects and normal subjects were observed for 2 min. The sensor generates output