Journal of Applied Biomedicine xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Journal of Applied Biomedicine

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

Segmentation and detection of physical activities during a sitting task in Parkinson's disease participants using multiple inertial sensors

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ARTICLE INFO

Article history:
Received 17 February 2017
Received in revised form 27 April 2017
Accepted 24 May 2017
Available online xxx

Keywords:
Parkinson's disease
Machine learning
Activity detection
Auto segmentation

ABSTRACT

Introduction: The development of inertial sensors in motion capture systems enables precise measurement of motor symptoms in Parkinson's disease (PD). The type of physical activities performed by the PD participants is an important factor to compute objective scores for specific motor symptoms of the disease. The goal of this study is to propose an approach to automatically detect the physical activities over a period time and segment the time stamps for such detected activities.
Methods: A wearable motion capture sensor system using inertial measurement units (IMUs) was used for data collection. Data from the sensors attached to the shoulders, elbows, and wrists were utilized for detecting and segmenting the activities. An unsupervised machine learning algorithm was employed to extract suitable features from the appropriate sensors and classify the data points to the corresponding activity group.
Results: The performance of the proposed technique was evaluated with respect to the manually labeled and segmented activities. The experimental results reveal that the proposed auto detection technique – by obtaining high average scores of accuracy (96%), precision (96%), and recall (98%) – is able to effectively detect the activities during the sitting task and segment them to the proper time stamps.

Introduction

Parkinson's disease (PD) is a degenerative and progressive movement disorder of the central nervous system (Jankovic, 2008). There are several motor symptoms associated with the disease including tremor, bradykinesia, dyskinesia, and rigidity. These motor symptoms can severely affect the normal activities of individuals with PD, particularly in advanced stages. Several medical therapies and surgical interventions such as deep brain stimulation (DBS) are suggested for the treatment of individuals with PD. However, the disease is progressive in many individuals in spite of such therapies. As the disease worsens, treatments need to be modified to provide clinically optimized therapy. Hence, it is essential to monitor PD patients over time in order to accurately modify the treatment and especially target this to the individual patient's need. Thus, patients are required to undergo frequent evaluations to measure motor symptom changes over time. At present, such evaluations have to be performed in the presence of and by an expert clinician in clinic.

The Unified Parkinson's Disease Rating Scale (UPDRS) performed by such an experienced clinician has been accepted as the gold standard for quantitative assessment of the PD motor symptoms. The main drawback of the UPDRS is that the severity of the motor symptoms is assessed subjectively by a human observer with low inter-rater reliability (Chien et al., 2006). This assessment serves as the gold standard for the evaluation of patients in the clinic to grade and categorize a patient's severity of disease. Despite the advances in the interventions for PD including DBS and potentially even more novel disease modifying treatments, the assessment has remained within the domain of clinical expert evaluation, which is at best scale-based and hence subjective.

The advancement of more complex interventions for PD, thus accentuates the need for improved assessment measures that are objective, quantitative, reliable, and portable. Employing a

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http://dx.doi.org/10.1016/j.jab.2017.05.002
1214-021X/

quantitative measurement for each motor symptom of PD can help clinicians monitor the patient more effectively and make better individualized clinical decisions. It is also possible to envision remote monitoring of patients that are unable to travel to the clinic. In such scenarios of telemedicine-based assessments, although the expert may be available for discussion, the assessment of the patient is performed in their local setting and often by a non-expert. As immobility advances, having an objective measurement system locally that would provide the expert a consistent assessment would be paramount in adjusting therapy.

Currently, few studies have explored quantitative measurement of motor symptoms in PD using inertial sensors (Dai and DAngelo, 2013; Delrobaei et al., 2014; Printy et al., 2014; Salarian et al., 2007). Inertial sensors have been used to measure bradykinesia (Cancela et al., 2010), motor-fluctuations (Keijsers et al., 2006), fall prevention (Moore et al., 2008) and walking speed (Lord et al., 2008). The quantitative assessment in such studies is mainly based on motion tracking sensors such as magnetic trackers, touch sensors, accelerometers, and gyroscopes. Accelerometer sensors have been widely used for action recognition due to their compact size and reliability (Godfrey et al., 2011). Accelerometers allow for continuous remote mobility monitoring of patients and can be used to evaluate the performance of in-home daily activities. However, the recorded sensor data is extensive and requires manual segmentation of the motor tasks. Briefly, the type of activity within an individual task is identified, and the time stamp for the corresponding activity is entered manually into a computer. Once completed, the mobility parameters associated with each motor symptom can be measured and analyzed.

Manually labeling the activities and segmenting the time stamps during the motor task such as sitting has been utilized as a gold standard. However, depending on how many tasks are done, this process can be very time consuming, and the chance of error is increased. For example, giving one sitting record to different examiners for segmentation, the results were slightly different from each other. Moreover, several examiners would have to be trained to do the time consuming manual segmentation. Thus, automatic detection and segmentation of the various motor tasks would reduce data processing time, reduce human error and may encourage a wider use of these sensors for assessment of PD.

A variety of auto activity detection techniques and their application in PD have been proposed (Godfrey et al., 2011; Moncada-Torres et al., 2014; Najafi et al., 2002; Nguyen et al., 2015a). These techniques are mainly based on standard signal processing methods, and activities such as *walking*, *sit-to-stand*, and *turning* were detected by processing and analyzing the signals from the sensors. The signals from such activities reveal significant temporal and spatial variations, allowing these activities to be detected using signal processing techniques. However, such techniques may not be helpful for detecting the activities during a sitting task since the signals associated with activities performed while sitting do not show considerable variations. Therefore, new approaches based on pattern recognition and machine learning need to be applied in these scenarios.

The central aim in pattern recognition is to employ machine learning and statistical techniques to classify various patterns and discover the regularities in data (Bishop, 2006). Applications of machine learning techniques are numerous and cover wide scopes with applications in medicine, image processing, business, and geology (Cao et al., 2016; Cobo et al., 2012; Kramar, 1995; Liu et al., 2014; Rustempasic and Can, 2013; Salari et al., 2013). For instance, an intelligent scoring system based on a novel machine learning structure was proposed in (Liu et al., 2014) to predict acute cardiac complications within 72 h for chest pain patients presented in emergency department. Authors in (Cao et al., 2016) recently proposed a novel method based on machine learning techniques for image analysis and image classification. Machine learning techniques are divided into two groups, namely supervised and unsupervised. Supervised techniques use the automatic learning approaches to extract the pattern from the empirical data, and sophisticated decisions can be made based on the learned behaviours. Support Vector Machine (SVM) (Cortes and Vapnik, 1995), decision tree (Utgoff, 1989), extreme learning machine (ELM) (Huang, 2015), and K nearest neighbours (Altman, 1992) are some well-known supervised learning techniques. On the other hand, unsupervised techniques aim to group the patterns which are similar to each other in a set of features without relying on the training samples. Cluster analysis is one of the major unsupervised techniques in pattern recognition. In hard clustering techniques such as K-mean (Hartigan and Wong, 1979), each data point is assigned to exactly one cluster. Fuzzy set theory proposed by Zadeh (Zadeh, 1965) determines the membership function; hence, data points are assigned to the proper cluster with respect to their degree of membership. However, one of the main drawbacks with clustering algorithms is determining the number of clusters.

In order to address the limitations mentioned for signal processing techniques in detecting and segmenting the activities while sitting, and avoid time consuming manual segmentation, we aim to use the pattern recognition technique to automatically and efficiently detect the motor activities done continuously during the sitting task in PD and control participants and segment the time stamps from the inertial sensor data.

Materials and Methods

Participants

Twelve PD participants were recruited from the Movement Disorder Center at the London Health Sciences Center. The inclusion criteria for the PD participants were: (1) idiopathic

Fig. 1. (a): Rest, (b): Posture, (c): Pronation-Supination.