A review of Parkinson's disease cardinal and dyskinetic motor symptoms assessment methods using sensor systems

Somayeh Aghanavesi, Jerker Westin

Dalarna University, Computer Science Department,
Rodavagen 3, S78188 Borlänge, SWEDEN
saa,jwe@du.se

Abstract. This paper is reviewing objective assessments of Parkinson's disease (PD) motor symptoms, cardinal, and dyskinesia, using sensor systems. It surveys the manifestation of PD symptoms, sensors that were used for their detection, types of signals (measures) as well as their signal processing (data analysis) methods. A summary of this review's finding is represented in a table including devices (sensors), measures and methods that were used in each reviewed motor symptom assessment study. In the gathered studies among sensors, accelerometers and touch screen devices are the most widely used to detect PD symptoms and among symptoms, bradykinesia and tremor were found to be mostly evaluated. In general, machine learning methods are potentially promising for this. PD is a complex disease that requires continuous monitoring and multidimensional symptom analysis. Combining existing technologies to develop new sensor platforms may assist in assessing the overall symptom profile more accurately to develop useful tools towards supporting better treatment process.

Keywords: Parkinson's disease; sensors; objective assessment; motor symptoms; machine learning; dyskinesia; bradykinesia; Rigidity; tremor.

1 Introduction

The number of studies using electronic healthcare technologies and sensor systems assessing the Parkinson's disease (PD) motor symptoms objectively are increasing. PD is a progressive neurological disorder characterized by a large number of motor symptoms that can impact on the function to a variable degree. The four cardinal motor symptoms of PD comprise of tremor, rigidity, bradykinesia and postural instability. The primary goal of therapy is to maintain good motor function. Therefore therapeutic decision making requires accurate, comprehensive and accessible quantification of symptoms. Electronic sensor-based systems can facilitate remote, long-term and repeated symptom assessments. They are able to capture the symptom fluctuations more accurately and also they are effective with patient's hospitalization costs. This paper reviews methods and sensor systems to detect, assess and quantify the four cardinal and dyskinetic motor symptoms. The method for identifying and accessing resources involved the online databases, Google Scholar, IEEE computer society, Springer link (Springer Netherlands) and PubMed central. The evaluation of resources was based on their relevance to the topic and the year of publication (not older than 2005). Selection of articles is done to have one reference per instrument that was used to detect all our addressed symptoms. The structure of this article is formed into sections of PD symptoms, followed by corresponding sensors and instruments, and computer and statistical methods that were employed for assessments.

2 Parkinson's disease cardinal and dyskinetic symptoms

Parkinson's tremor consists of oscillating movements and appears when a person's muscles are relaxed and disappears when the person starts an action. It's the most apparent well-known symptom. Rigidity symptoms cause stiffness of the limbs, neck or trunk and result in inflexibility. Bradykinesia (slow movement) describes the general reduction of spontaneous movement (abnormal stillness and a decrease in facial expressivity) and causes difficulties with repetitive movements. It can cause walking with short and shuffling steps and can also affect the speech. Postural instability symptom is a trend to be unstable when standing upright, rising from a chair or turning. And dyskinesia is a difficulty in performing voluntary movements, which often occurs as a side effect of long-term therapy with levodopa. Dyskinetic movements look like smooth tics (uncoordinated periodic moves).

3 Sensors, signals and measures

Among the developed electronic techniques to measure and analyze the PD's symptoms the common sensors and devices for evaluation are accelerometer, electromyograph (EMG), magnetic tracker system, gyroscope, digitizing tablet, video recording, motion detector, and depth sensor. In accelerometry, an electromechanical sensor device is used to measure acceleration forces and capture the movements by converting it into electrical signals that are proportional to the muscular force producing motion. Gyroscope is a sensor device used to measure angular velocity (angular rate) which senses rotational motion and changes in orientation [1]. Accelerometer and gyroscope are joint in many motion sensing instruments. Electromyography (EMG) is a technique for evaluating and recording the electrical activity produced by neurologically activated muscles using Electromyograph that records how fast nerves can send electrical signals. Digitizing tablet in PD symptom detection is a computer input device used to digitize patient's drawing when he/she traces a pre-drawn shape [2], [3] or freely writes or draws a shape. The position of the tip of the pen (x, y) and the time (milliseconds) are collected for analysis [3]. Electromagnetic tracker system captures the object's movement displacement (x, y, and z) and orientation (pitch, roll, and yaw). Active optical marker systems are used to capture and record object's motion. Wired position markers can be placed on different locations of patient's body to obtain object's posture and movements.

4 Signal processing and analysis

Wavelet transform as a multi-resolution transformation method uses a variable window size at each level to obtain more information about the sensor signal in the time-frequency (time-scale) domain. Principal component analysis (PCA) is theoretically the best linear dimension reduction technique that uses rectangular transformation to convert the set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables [3]. It's the direction to where the most variance exists. Wavelet transform is usually used with PCA to reduce the number of features to most important and related ones [3]. Discrete Fourier Transform converts samples of a function (a signal that varies over time) into the list of coefficients of a finite combination of complex sinusoids (ordered frequency that has sample value). Fast Fourier transform converts time (signal) to frequency by decomposing an N point time domain signal into N signals [4] and Detrended Fluctuation Analysis is a method to determine self-affection of a signal [5]. Often Spectral Analysis (SA) is used in signal processing for PD's motor symptom assessment. The magnitude of an input signal versus a certain frequency within the full range of the frequency is measured using a spectrum analyzer. Artificial Intelligence (Visual perception, decision making, image processing, and classification techniques) enables the development of computer systems to perform tasks that usually require human intelligence. For image processing, computer vision is a method to acquire, process and analyze a patient body's images (like face and body posture). Machine learning in PD symptom assessment [6] often includes techniques to assess the magnitude of addressed symptom. Linear discriminant analysis (LDA) classification method is used to optimally separate populations and reduce the dimensionality [7], [8]. Non-parametric, generalized and multilayer perceptron analysis are different alternatives of LDA.

5 Discussion and conclusion

Table 1 summarizes the research studies that have evaluated the four cardinal PD motor symptoms. From left to right, it lists the evaluated symptoms, type of the instruments, calculated measures and employed analytical assessment methods.

Table 1. An overview of research studies articles that objectively assess PD motor symptoms and dyskinesia (Spectral Analysis is abbreviated as SA, and three dimension as 3-D).

Symptom	Instrument	Measure	Method	Reference
Tremor	Smartphone (3-D accelerometer, timer, finger tappning sensor)	X and Y coordinates, Time duration, 3-D Acceleration	Random forest machine learning technique, Detrended analysis	[5], 2015
	Pen stylus	Acceleration	Non parametric	[9], 2013
Rigidity	Real time wearable sensor	Acceleration	Shank, Ankle, Knee signal SA	[10], 2010
	Custom made goniometer	Angular velocity	SA of vertical leg acceleration	[11], 2010
	Stride monitor system	Acceleration	Extension-flexion-component analysis	[12], 2008

	Isokinetic dynamometer Biodex System 3	3-D angular velocity, Anatomical zero	Spearman correlation	[13], 2014
Dyskinesia	Digitized tablet (Spirography)	Velocity of drawing movements	Standard deviation analysis of drawing velocity	[2], 2005
	Wrist accelerometer	Trunk acceleration, Shank velocity	Support vector Machine learning	[6], 2012
	Wrist-worn inertial sensor	Median angular velocity of trunk Rotation	Linear discriminant analysis	[7], 2015
Postural instability	MTX Xsens sensor with 3-D accelerometer and 3-D gyroscope	Acceleration, Direction and Distance	Antero-posterior (AP), Medio-lateral (ML), and Vertical directions analysis	[14], 2011
	Motion detector, Depth sensor, Vicon, motion capture system and Force plate	Ground reaction force, Body center of mass, Displacement, Velocity	Segmental method, Zero-point-to-zero-point integration technique	[15], 2014
	Digital angular-velocity transducer	Velocity (pitch, roll, angle), Time	Linear discriminant analysis, Anova	[8], 2005
	Accelerometer	Acceleration	Posture contextualization algorithm	[16], 2014
Tremor and Dyskinesia	Accelerometer, Gyroscope, Infrared camera	Acceleration, Angular velocity and time	Genetic Algorithm spectral classification	[20], 2014
Tremor and Bradykinesia	Miniature uni-axial gyroscope	Angular velocity in roll, yaw and pitch direction	Biomedical signal processing (Spectrum Analysis)	[1] , 2007
Tremor and Postural instability	Accelerometer	Mean velocity, Acceleration range, Mean acceleration	Hilbert–Huang transformation of postural parameters	[17], 2011
Bradykinesia and Dyskinesia	Digitized tablet (spiral and tapping) Pocket PC device	Radius, Time, Mean speed of correct proportion of taps	Wavelet transform and principal component analysis	[3], 2010
	Ambulatory Multichannel accelerometer, Video recorder	Acceleration, Body position, Time, Gravitational force, Body segment angel	Direct current component, Discriminant, variance (Anova), regression analysis	[18], 2005
	Kinetigraph(3-D accelerometer)	Time period, Wrist acceleration	Expert system approach	[19], 2012
Rigidity, Bradykinesia and Dyskinesia	Digitized tablet with finger tapping and Spirography	Speed, Accuracy, Standard deviation of radial drawing velocity	Principal component analysis	[4], 2010

According to table 1, rigidity and postural instability are mostly evaluated as single symptoms. However, among articles which research on combined symptoms assessments, bradykinesia (with tremor, dyskinesia, rigidity, and dyskinesia together) is mostly studied. Tremor is assessed in some studies as a single symptom, and also together with each of bradykinesia, dyskinesia, and postural instability symptoms.

A common sensor for symptom detection was the accelerometer that was mostly used for detecting the tremor, dyskinesia, and postural instability. Digitizing tablet is used almost for all types of symptoms. Smartphone [5] and Microsoft Kinect (motion detector, and depth sensor) [15] are the latest devices in the market used for this. Smartphones (new generation of sensing devices) could expand rapidly with PD motor symptom assessments. Angular sensor detectors are used to detect rigidity and postural instability as single symptoms, and they are also used to detect bradykinesia and dyskinesia together with tremor. Video recording is often required for clinicians' observational analysis. Wearable sensors (small, available, accurate, including high time resolution, and flexible with body locations) are preferred for PD since it's a progressive chronic disease and symptoms need to be assessed continuously throughout the day. For this, the mobile applications and wrist watches are more preferred as they are currently part of almost everyone's daily accessories. However, their analysis methods and their validations are important and a question is whether the devices or clinical ratings will become the gold standard. Machine learning techniques are potentially good solutions in the development of assessment systems to determine the effectiveness of drug dosing. Tools that can effectively characterize the severity of symptoms and can discriminate between bradykinesia and dyskinesia are needed. Some successful products are Parkinson's Kinetigraph [18] , Kinesia devices [20], and Rempark [6].

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