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Research Article

Automated Assessment of Motor Impairments in Parkinson's Disease

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Abstract

A system for the automatic assessment of motor impairments in Parkinson's Disease (PD) is presented. The interface, built around optical RGB-Depth devices, allows for tracking of hands and body movements during the performance of standard upper and lower limb tasks, as specified by the Unified Parkinson's Disease Rating Scale (UPDRS). The assessment of the different tasks is performed by machine learning techniques. Selected kinematic parameters characterizing the movements are input to trained classifiers to rate the motor performance. The accurate tracking and characterization of the movements allows for an automatic and objective assessment of the UPDRS tasks, making feasible the monitoring of motor fluctuations also at-home for telemedicine or neurorehabilitation purposes.

Keywords: Parkinson's disease; Movement disorders; UPDRS; Automated assessment; Natural human computer interface; RGB-Depth; At-home monitoring; Hand tracking; Body tracking

Introduction

Parkinson's Disease (PD) is a neurodegenerative disease characterized by a progressive motor impairments, whose severity is subjectively assessed by clinicians during the performance of standard motor tasks usually defined by the motor examination section of the Unified Parkinson's Disease Rating Scale (UPDRS) [1,2]. Objective and automatic assessment of the tasks at-home can improve the reliability of the assessment, generally influenced by inter-rater disagreements [3], and could allow a weekly adjustment of the therapy, reducing fluctuations [4,5]. Proposed solutions for the automatic assessment of PD motor tasks make use of the established correlation existing between kinematic characteristics of the movements and the severity of the impairment [4,5], mainly by technologies based on optical devices and wearable sensors [6,7]. Approaches based on wearable sensors require the involvement of the patient for the initial setup and, possibly, for the calibration phase, are usually uncomfortable for impaired people and their invasiveness can affect functional performance [8,9]. On the contrary, optical approaches based on recent RGB-Depth devices are less invasive and allow for accurate measurements, so they have been proposed for tracking the body and hand movements in the framework of PD assessment [10,11].

In this context, we present a low-cost system for the automatic and at-home assessment of some of the upper and lower limb tasks of the UPDRS, namely Finger Tapping (FT), Opening-Closing (OC) of the hand and Pronation-Supination (PS) of the hand, Sit-to-Stand (S2S) and Leg Agility (LA). The system implements a non-invasive gesture-based Human Computer Interface (HCI), which allows people with motor impairments both to interact with the graphical interface of the system through simple gestures such as opening and closing of the hand or pointing with fingers on interactive objects, and the tracking of hands and body movements, for the assessment of the motor performance during the performance of standard UPDRS tasks.

In particular, the developed algorithm for the hand tracking has proved to be more robust and accurate for fast movements respect to other solutions based on proprietary algorithms provided by commercial devices [10], making the assessment more reliable. In addition, the algorithm for the hand tracking does not depend on any particular device or proprietary Software Development Kit (SDK), but requires only the RGB and depth information availability at a proper frame rate. Results on experiments performed to validate the system are presented: the accuracies obtained in the automatic assessment of the considered UPDRS tasks, as compared to the clinician standard assessment, demonstrate the feasibility of the system also for the at-home remote monitoring of PD motor impairments.

Patients and Methods

Two cohorts of 44 PD patients (mean Hoehn and Yahr score 2.3, min 1, max 4; age 41-85 years; disease duration 1-29 years), and 15 Healthy Control (HC) subjects respectively (age 45-78 years) were recruited. Patients were excluded if they had tremor severity >1 or cognitive impairment (Mini-Mental State Examination Score <27/30). All subjects provided their informed consent prior to their participation. The PD cohort was assessed by two neurologists with experience in movement disorders.

The system hardware consists of two different setups: a near mode operation setup for the capture and the assessment of upper limb tasks, and a far mode setup for the capture and the assessment of lower limb tasks.

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The near mode setup is based on low-cost short-range RGB-Depth device (Intel RealSense SR300©) and black lightweight gloves with colour markers imprinted on them; each marker corresponds to a specific part of hand to be tracked for specific system actions (i.e., colour calibration, selection of the task to be executed) (Figure 1A and B). The short-range device acquires the RGB and depth streams to be processed. After some calibrations (image brightness, color), the custom software performs the real-time hand and finger tracking by fusion of both colour (RGB) and depth information from the streams [10]. The 3D position of the hand centroid is estimated from the depth stream, and it is used to coarsely segment the hand from the background. Every color marker area is then reprojected on the corresponding 3D point cluster, and the 3D cluster centroids are then evaluated to estimate the 3D position of the fingers and the hand in real time. This information is used both for the movement analysis and to implement the gesture-based human computer interface for the management of the system.

Figure 1A: System setup for the near mode (upper limb tasks). Colored gloves are used for the tracking and for computer interactions (for example to select actions by moving and closing the hand on drawn squares). Position of hand 3D centroid (solid white point); colored markers on glove; hand 3D bounding box with centroid (solid magenta line and point).

Figure 1B: Example of HCI for upper limb task selection: exercise is selected by moving the hand on interactive objects (object color changes from white to red) and closing the hand to confirm the choice.

The far mode setup is based on long-range RGB-Depth device (Microsoft Kinect v.2©) (Figure 2A and B).

The skeleton tracking capabilities provided by the SDK of Microsoft Kinect v.2© are used both for the analysis of body movements and for the coarse tracking of the bare-hand position. In this case, some simple gestures such as raising the hand and shaking it, or positioning the hand on interactive objects, are used for the interaction with the system.

The automatic assessment of the UPDRS tasks makes use of some kinematic parameters automatically estimated from the movements of several body parts: fingertips and palm for the upper limbs; femur, knee, tibia and spine for the lower limbs. While for the upper limbs the 3D trajectories of fingers and hand are directly tracked by the algorithm we developed [12], for lower limbs we use the 3D joint coordinates of hip, knee and ankle provided by the Microsoft Kinect SDK in the form of a skeletal model of the body (Figure 2A) [13,14]. In particular, we focus our attention on SpineS, HipC, HipR/L, KneeR/L and AnkleR/L joints, useful for the assessment of the lower limbs tasks as indicated by the UPDRS guidelines (Figure 2B). Specifically, we use the angle between femur and tibia segments (segments HipR/L-KneeR/L and KneeR/L-AnkleR/L) for the LA task and the angle between the spine segment (i.e., SpineS - HipC) and the vertical direction for the S2S task (Figure 3A and B). The vector Pof selected parameters we have considered is related to typical motor features implicitly taken into account by neurologists to score the patient performance: amplitude, speed, rhythm variation and typical anomalies in parkinsonian patients such as hesitations, "freezing" or partial movements.

All the patients were evaluated for the FT, OC and PS upper limb tasks, and for the S2S and LA lower limb tasks, according to the standard UPDRS scoring rules. At the same time, the motor performances of the PD patients were tracked by the system and the related kinematic parameters were automatically extracted. The HC subjects performed the same tasks, in the same environ-mental conditions and with the same system setup of PD patients.

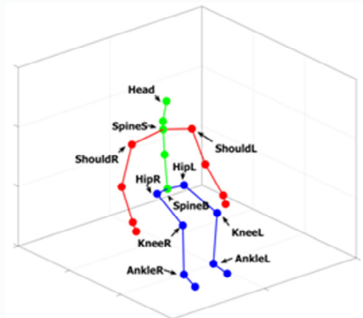

Figure 2A: Far mode setup (lower limb tasks). Positions of SDK joints in the 3D skeleton representation and superimposed on the RGB image. 3D position of skeletal joints provided by the device SDK related to lower limb tasks examined.

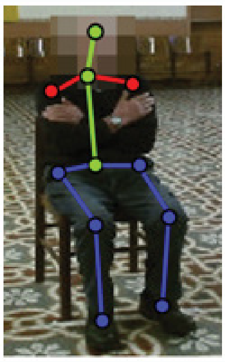

Figure 2B: 2D joints of the skeleton model superimposed on the RGB Image in sitting position.

Figure 3A: Somebody segments and joints involved in Leg Agility analysis (example of sagittal knee angle).

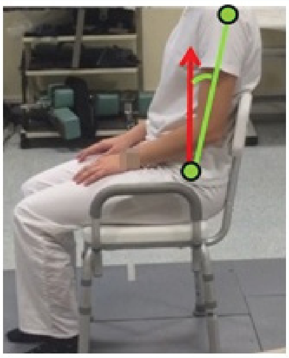

Figure 3B: Somebody segments and joints involved in Sit To Stand analysis (example of sagittal trunk angle).

Results

The most discriminative parameters identified for every UPDRS tasks are shown in Table 1. Principal Component Analysis (PCA) was applied to the initial set of kinematic parameters of every task to filter out those ones contributing for less than 5% to the total information and to reduce the intrinsic redundancy among them. Then, the remaining parameters were correlated (using the Spearman's correlation coefficient ρ) to the neurologist UPDRS scores of the motor performances for all the subjects of the PD cohort, keeping only those parameters showing a good correlation at significance level $p<0.01$. The feature selection procedure allowed us to reduce the initial set of parameters significantly for each task: from 20 to 12 parameters for FT; from 20 to 10 for OC; from 20 to 8 for PS; from 10 to 6 for LA; from 8 to 4 for S2S.

As expected, on the average, the HC subjects performed better respect to PD subjects for all the tasks. Hence, the average parameters P-HC of the HC subjects were used to normalize the P-PD ones, giving the normalized PD parameters P-PD-norm of equation: P-PD norm = P-PD/P-HC.

As a consequence, most of these parameters result able to discriminate the different UPDRS severity classes for each specific task, highlighting the increasing level of severity of the motor impairment with the corresponding increasing of the values of the components of P. This is also visually confirmed by the radar graphs in Figure 4 for all the considered tasks, in which normalized kinematic parameters are represented from 0 (that corresponds to the best value, in general associated to HC group) to 1 (that corresponds to the worst value, in general associated to the most severe PD group): the increasing severity of motor performances is highlighted by the expansion of the corresponding radar graph that represents the mean values of the selected parameters P, drawn in the [0-1] range and indicated as Z values, both for the HC subjects and the UPDRS severity classes of the subjects in the PD cohort.

The results shown in Figure 4 concerning the discriminant power of the selected kinematic parameters respect to different PD classes make them suitable for the automatic assessment of the UPDRS tasks. In order to achieve this goal, five data sets consisting of "vector of parameters P - neurologist UPDRS score" pairs from the PD cohort were used to train five different supervised classifiers, one for each UPDRS task. In particular, the LIBSVM library package [15] was used to implement five Support Vector Machine (SVM) classifiers with polynomial kernel: each classifier was trained by the corresponding set of pairs to create a predictive model and to learn how to automatically evaluate new instances of parameters, this for

Table 1: Discriminative parameters identified for every UPDRS upper and lower Limb Tasks.

Name	Meaning	Units	Correlation coefficient ρ-values
TASK FT			
Z1, Z2[1]	Max Finger Opening (mean and CV)	[mm, -]	-0.44, 0.34
Z3, Z4[1]	Max Finger Amplitude (mean and CV)	[mm, -]	-0.43, 0.38
Z5[1]	Total Duration of FT movements (CV)	[-]	0.43
Z6, Z7[1]	Max Finger Opening Speed (mean and CV)	[mm/s, -]	-0.57, 0.38
Z8, Z9[1]	Max Finger Closing Speed (mean and CV)	[mm/s, -]	-0.59, 0.41
Z10	Main Frequency (Voluntary Movement band)	[Hz]	-0.47
Z11[1], Z12[1]	Duration of Finger Opening and Closing (CV)	[-, -]	0.46, 0.45
TASK OC			
Z1, Z2[1]	Max Hand Opening (mean and CV)	[mm, -]	-0.60, 0.43
Z3, Z4[1]	Max Hand Amplitude (mean and CV)	[mm, -]	-0.57, 0.51
Z5, Z6[1]	Duration of OC movements (mean and CV)	[s, -]	0.30, 0.56
Z7, Z8[1]	Max Hand Opening Speed (mean and CV)	[mm/s]	-0.62, 0.54
Z9, Z10[1]	Max Hand Closing Speed (mean and CV)	[mm/s]	-0.55, 0.52
TASK PS			
Z1Z2[1]	Max Hand Rotation (mean and CV)	[degree, -]	-0.37, 0.31
Z3, Z4[1]	Max Hand Supination Speed (mean and CV)	[degree/s, -]	-0.45, 0.35
Z5, Z6[1]	Max Hand Pronation Speed (mean and CV)	[degree/s, -]	-0.47, 0.43
Z7	Main Frequency (Voluntary Movement band)	[Hz]	-0.46
Z8[1]	Duration of Pronation movements (CV)	[-]	0.35
TASK LA			
Z1, Z2[1]	Max Knee Angle (mean and CV)	[degree, -]	-0.59, 0.47
Z3	Mean Speed	[degree/s]	-0.67
Z4, Z5[1]	Duration (mean and CV)	[s, -]	0.24, 0.25
Z6	PoorMovements	[#]	0.7
TASK S2S			
Z1	Maximum Bending Angle	[degree]	0.63
Z2	Mean Speed of movement	[degree/s]	-0.62
Z3	Duration of movement	[s]	0.75
Z4	Peaks of Trunk Bending	[#]	0.64

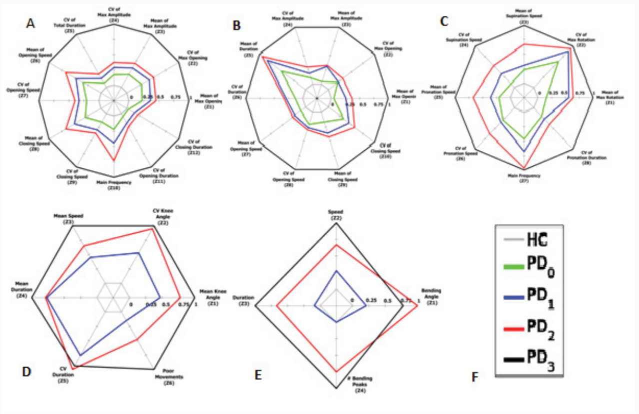

Figure 4: Radar graphs of HC and PD severity classes vs. mean parameter values for upper and lower limbs UPDRS tasks. PD classes range from UPDRS 0 (no impairment) to UPDRS 3 (moderate impairment).
A) Finger Tapping, B) Opening-Closing, C) Opening-Closing, D) Leg Agility, E) Sit To Stand, F) List of classes

every specific task, and in agreement with the standard neurological assessment of the motor performance expressed by UPDRS score. The classification accuracy in assigning correctly the UPDRS scores to new sets of parameters was tested by using the leave-one-out cross validation method, and the resulting confusion matrices were used to characterize the classification performance of each classifier. The classification errors, considered as the absolute difference between the observed and predicted UPDRS severity score, were few in number and limited to one UPDRS score. The classification accuracies, obtained from the confusion matrices, were about 80% for FT; 72% for OC; 74% for PS; 60% for LA; and 58% S2S respectively. Assuming the automatic assessments by the system as neurological scores of a third clinician rater, the results for upper limbs can be considered satisfactory as compared to standard inter-rater agreement [3]. A slightly worse performances of the lower limb classifiers is however present, probably due to the small number of training samples and the scarcely discriminant power of some parameters (e.g., Z4 and Z5 for LA; Z1 for S2S).

Discussion

This work presents a system for the automatic and objective assessment of PD patients performing standard UPDRS tasks, which could be suitable for the at-home monitoring of the motor performance. The system is non-invasive and low-cost: it is based on a gestural human computer interface that allows, at the same time, both the self-management of the system and the motor performance evaluation according to the UPDRS guidelines. The assessment is performed by supervised classifiers, which are trained on the selected kinematic parameters estimated from the patient's movements.

The automated assessments of the task performances are, on the whole, in good agreement with the clinical ones. At this stage, classification accuracies appear more satisfactory for upper limb tasks, making the system suitable for self-administrated assessment of UPDRS tasks at-home. Instead, further work has to be done both to improve the accuracy in the assessment of the lower limb tasks. A further step would also require estimating the effect of different datasets coming from different raters on the classification accuracy of each classifier. In addition, the system usability has to be verified in real home environments, with people suffering of motor impairments and, in general, with poor skill in the use of technologies.

In conclusion, the proposed solution represents a first step toward a more comprehensive, objective and automated assessment of the motor status in PD. The approach could be suitable for the at-home monitoring of the disease, with consequent benefits for the patients and increased cost-efficiency for the health care system. Besides, the approach could also be extended to other neurological, pathological and non-pathological conditions characterized motor impairments.

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