Steps toward Automatic Assessment of Parkinson’s Disease at Home

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Abstract*—This work presents a non-invasive low-cost system suitable for the at home assessment of the neurological impairment of patients affected by Parkinson’s Disease. The assessment is automatic and it is based on the accurate tracking of hands and fingers movements of the patient during the execution of standard upper limb tasks specified by the Unified Parkinson’s Disease Rating Scale (UPDRS). The system is based on a human computer interface made by light gloves and an optical tracking RGB-Depth device. The accurate tracking and characterization of hands and fingers movements allows both the automatic and objective assessment of UPDRS tasks and the gesture-based management of the system, making it suitable for motor impaired users as are PD patients. The assessment of UPDRS tasks is performed by a machine learning approach which use the kinematic parameters that characterize the patient movements as input to trained classifiers to rate the UPDRS scores of the performance. The classifiers have been trained by an experimental campaign where cohorts of PD patients were assessed both by a neurologist and the system. Results on the assessment accuracy of the system, as compared to neurologist’s assessments, are given along with preliminary results on monitoring experiments at home.

Keywords-Parkinson’s disease; UPDRS assessment; RGB-D camera; hand tracking; human computer interface; machine learning; tele-monitoring

I. INTRODUCTION

Parkinson’s Disease (PD) is a chronic neurodegenerative disease characterized by a progressive impairment in motor functions (e.g., bradykinesia) [1] , with important impacts on quality of life. Unified Parkinson's Disease Rating Scale (UPDRS) [2] is commonly used by neurologists to assess the severity of the disease, whose motor aspects are an important part. Specifically defined motor tasks are used by neurologists to assess impairments and to assign a subjective score for each task on a scale of five classes of increasing severity.

The assessment process takes into account specific kinematic aspects of the movements (amplitude, speed, rhythm, hesitations) which are qualitatively and subjectively evaluated by neurologists. On the other hand, a quantitative and objective assessment of the tasks is important to increase the reliability of the clinical assessment [3]. A commonly adopted solution is to make use of the well-established correlation existing between kinematic parameters of the movements and the severity of the impairment [4][5]. This correlation is used in the automatic and objective assessment of UPDRS motor tasks by several technological approaches, among which those based on optical devices and wearable inertial sensors [6][7].

Drug treatment of the PD symptoms is crucial to reduce the effects of the impairment in daily activities but, because of possible fluctuations in impairment, it would be desirable to adjust the therapy on a weekly basis, both for the best effectiveness and to reduce side and long term effects [8]. Unfortunately, the cost of a traditional weekly assessment, preferably at home to reduce patient’s discomfort, is unsustainable for the health care system. In this context, technology can support neurologists with an objective and quantitative assessment of UPDRS motor tasks. Focusing on the upper limb tasks of UPDRS, solutions based on wireless inertial measurement devices (accelerometers and gyroscopes) [8]-[10] and on resistive bend sensors [11] do not suffer of occlusion problems but they are more uncomfortable for motor impaired people respect to optical approaches and, more important, their invasiveness can affect motor performance.

Optical approaches for hand tracking of motor impaired people and for the automatic assessment of upper limb tasks of UPDRS, namely Finger Tapping (FT), Opening-Closing (OC) and Pronation-Supination (PS), have been recently proposed based on RGB cameras [12], passive markers [13] and bare hand tracking by consumer depth sensing devices [14]-[17].

Less attention is generally given to the assessment of the tracking accuracy obtainable by the proprietary hand-tracking firmware of these consumer devices. Their accuracy can be unsatisfactory especially for fast movements, as has been shown by comparisons with standard optoelectronic systems [18]; nevertheless, this is an important requirement to be considered for the reliability of kinematic parameters and the motor performance assessment. Furthermore, the short product life span of these devices and of the related

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Software Development Kit (SDK) warns against solutions too dependent on proprietary hardware and software. Along this line of research, we present a low-cost system for the automatic assessment of the upper limb UPDRS tasks (FT, OC, PS) at home. The system hardware is based on lightweight coloured gloves, a RGB-Depth sensor and a monitor, while the software implements 3D tracking of the hand trajectories, characterizes them by kinematic features and assesses the motor performance by trained Machine Learning algorithms. The software performs the real-time tracking by fusion of both colour and depth information from the RGB and depth streams. The system acts at the same time as a non-invasive Human Computer Interface (HCI) which allows motor impaired PD patients to self-manage the test execution. Respect to other approaches, based only on depth information and proprietary algorithms, the hand tracking is more robust and accurate for fast movements [18], making the final assessment more reliable. Another important characteristic of our solution is that it does not relay on any particular hardware or SDK; it assumes the availability of RGB and depth streams at reasonable frame rate. The accuracies obtained by the classifiers demonstrate the feasibility of the system in remote assessment of upper limb UPDRS tasks. Some preliminary results on at-home monitoring of PD patients are given.

The paper is organized as follows. The technological solution and the methodological approach for the accurate tracking of hand and fingers movement are described in Section II. Section III reports the results of the automatic classification of motor performance and some preliminary data about the assessment of patient's performance at home. Conclusions and future work are discussed in Section IV.

II. Systems and Methods

A. *System Hardware*

The hand/fingers tracking hardware consists of a low-cost RGB-Depth device (Intel Realsense SR300 ©) that provides synchronized RGB color and Depth streams at resolutions of 1920x1080 (Full HD) at 30fps and 640x480 (VGA) at 30 fps (max. 200) respectively. The RGB-Depth device is connected via a USB port to a personal computer (PC) running Microsoft Windows and equipped with a monitor positioned in front of the user (Figure 1). The monitor provides the visual feedback of the HCI for the hand and finger movements of the user. The user equipment consists of black lightweight gloves with imprinted colour markers: each colour marker corresponds to a particular part of hand to be tracked (e.g., fingertips and wrist) or to be used for colour calibration and system interaction (e.g., palm).

The device drivers and our developed software are used to implement both the hand and fingers tracking and the user interface of the HCI. The software running on the PC implements the data stream acquisition and processing for the hand/fingers tracking, the kinematic parameter estimation and the task assessment. Furthermore, the data produced in every test session, including video sequence of each performance, kinematic parameters and system scores are automatically encrypted and archived for further analysis and for clinician independent supervision and assessment.

Figure 1. Hand/fingers tracking system

B. *Initial Setup*

Global image brightness adjustment, hand segmentation and colour calibration for marker segmentation are performed during the initial setup phase. The Intel LibRealSense library is used for RGB and depth stream acquisition and the OpenCV library [19] is used to recover the 3D position of the hand centroid from the depth stream. A hand shaking movement of the user starts the recovering of the initial hand position. The hand centroid is used to segment the hand from the background and to define 2D and 3D hand bounding boxes, both for colour and depth images. Then RGB streams are converted from RGB to the HSV colour space, more robust to brightness variations. The design of the colour markers and the implementation of a colour constancy algorithm compensate for different ambient lighting conditions found in domestic environments. For this purpose, during the initial setup the white circular marker on the palm is detected and tracked in the HSV stream. The average levels of each HSV component of the circular marker are used to compensate for predominant colour components due to different types of lighting. Their values are used to scale each of the three HSV video sub-streams during the tracking phase.

C. *Hand and Finger Tracking*

During the tracking phase, the 3D position of the hand centroid is used to continuously update the 2D and 3D hand bounding boxes (Figure 2). The colour thresholds selected during the setup phase are used to detect and track all the color blobs of the markers. To improve performance and robustness, the CamShift algorithm [19] has been used in the tracking procedure. The 2D pixels of every color marker area are re-projected to their corresponding 3D points by standard re-projection, and their 3D centroids are then evaluated. Each centroid is used as an estimate of the 3D position of the corresponding part of the hand that is used for movement analysis.

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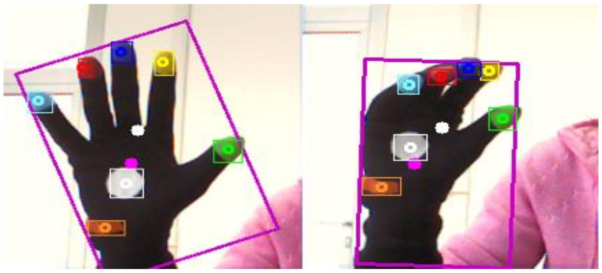

Figure 2. Hand segmentation and marker detection: color blob centroids and bounding box

D. Human Computer Interface for System Management

The real-time hand/fingers tracking software and the graphical user interface realize the human computer interface (Figure 3) where the patient can manage the test session (e.g., start and end the session, select the specific task, input information, etc.) by making simple gestures (opening and closing the hand, pointing with fingers) towards the graphical menu displayed on the monitor.

E. Clinical Assessment and Data Acquisition

The system performance was evaluated on two cohorts; one made up of forty patients (22 females, 18 males) with a diagnosis of Parkinson's Disease (PD), and the other made up of fifteen Healthy Control (HC) subjects. Patients were recruited according the UK Parkinson's Disease Society Brain Bank Clinical Diagnostic standards and met the following criteria: Hoehn and Yahr score (average 2.2, min 1, max 4); age 43–81 years; disease duration 2–29 years. Patients were excluded if they had previous neurosurgical procedures, tremor severity > 1 (UPDRS-III severity score), or cognitive impairment (Mini–Mental Score < 27/30). The HC subjects met these criteria: age, 35–78 years, not affected by neurological, motor and cognitive disorders. All subjects provided their informed consent prior to their participation.

The PD cohort was assessed for the FT, OC and PS UPDRS tasks on both hands by one neurologist expert in movement disorders and the resulting UPDRS severity scores were found between 0 (normal) and 3 (moderate impaired). The performance of the PD patients were tracked at the same time by the system and the related kinematic parameters of the hand/fingers trajectories were automatically extracted. The HC subjects performed the tests in the same environmental conditions and with the same system setup of PD patients.

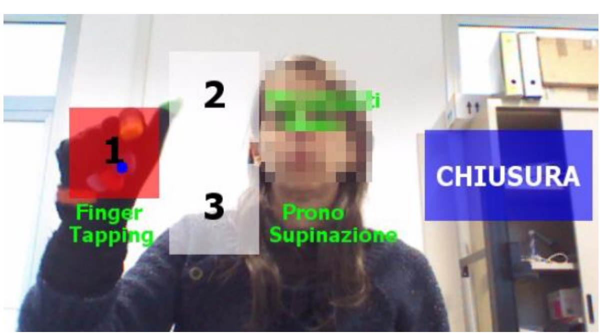

Figure 3. Human computer interface with natural gestural interaction

F. Kinematic Parameter Selection

The automatic assessment of UPDRS tasks makes use of the well establish correlation existing between the kinematic parameters of the movements, objectively evaluated by the system, and the severity of the impairment, subjectively rated by neurologists and expressed as UPDRS scores [4]. The kinematic parameters we choose are closely related to the typical characteristic of the patient movement that are used by neurologists to score the performance (amplitude, speed, rhythm, hesitations, and others). To compact the information associated to the parameters and to reduce their redundancy the most discriminative ones among them have been identified for every UPDRS tasks. First, a Principal Component Analysis (PCA) was applied to the initial set of parameters to filter out those which contribute less than 5% to represent the whole dataset. Then, the selected kinematic parameters were correlated to neurologist UPDRS scores (Spearman's correlation coefficient ρ), keeping only those ones with the best correlation with neurologist UPDRS scores, at significance level $p<0.01$ (Table I). Note that the choice of the parameters is such that increasing values of the parameters indicate a worsening of the performance.

In this context, the kinematic parameters of the HC subjects have been used to normalize the PD ones. Thanks to the better performance of HC subjects, their average score values $\mathbf{p_i}_{\,HC}$ are always better than the $\mathbf{p_i}_{\,PD}$ ones, and are used to obtain normalized PD parameters ($\mathbf{p_i}_{\,PD\,norm} = \mathbf{p_i}_{\,PD} / \mathbf{p_i}_{\,HC}$). This selection process produces normalized parameters which are able to discriminate UPDRS classes for the FT, OC and PS, highlighting the increasing severity of motor performance by the corresponding increasing of their values. This is visually confirmed by the mean values of the selected kinematic parameters versus UPDRS severity class as shown in the radar graphs of Figure 4(a) for FT, Figure 4(b) for OC and Figure 4(c) for PS tasks respectively. UPDRS classes for the FT, OC and PS, highlighting the increasing severity of motor performances by the corresponding expansion of the related radar graph representation.

G. Automatic UPDRS Assessment by Machine Learning

To implement the automatic assessment of the FT, OC and PS UPDRS tasks, three data sets of "parameter vector – neurologist UPDRS score" pairs were used to train three different classifiers. We use the LIBSVM library package [20] to implement three Support Vector Machine (SVM) classifiers with polynomial kernel. Their accuracy in assigning correctly the UPDRS scores was tested by using the *leave-one-out* cross validation method. The confusion matrices were used to characterize the classification performance of the SVM classifiers.

An interesting feature offered by the SVM classifier implementation is that, given the kinematic parameters vector as input, the classifier output is the vector **P** of probabilities **p**j that the input vector belongs class Cj. To test the classifiers and build the confusion matrices the class Ck corresponding to the highest probability **p**k among all the probabilities in **P** is chosen.

TABLE I. SELECTED KINEMATIC PARAMETERS

Name	Finger Tapping UPDRS task		
	Meaning	***Unit***	***ρ-value***
X_1	Maximum opening (mean)	mm	-0.43
X_2	Maximum opening (CV)	-	0.35
X_3	Maximum amplitude (mean)	mm	-0.41
X_4	Maximum amplitude (CV)	-	0.39
X_6	Duration (CV)	-	0.42
X_9	Maximum opening velocity (mean)	mm/s	-0.58
X_{10}	Maximum opening velocity (CV)	-	0.39
X_{11}	Maximum closing velocity (mean)	mm/s	-0.55
X_{12}	Maximum closing velocity (CV)	-	0.43
X_{13}	Main Frequency	Hz	-0.48
Name	**Opening-Closing UPDRS task**		
	Meaning	***Unit***	***ρ-value***
X_1	Maximum opening (mean)	mm	-0.54
X_2	Maximum opening (CV)	-	0.34
X_3	Maximum amplitude (mean)	mm	-0.55
X_4	Maximum amplitude (CV)	-	0.31
X_5	Duration (mean)	s	0.25*
X_6	Duration (CV)	-	0.58
X_9	Maximum opening velocity (mean)	mm/s	-0.63
X_{10}	Maximum opening velocity (CV)	-	0.47
X_{11}	Maximum closing velocity (mean)	mm/s	-0.54
X_{12}	Maximum closing velocity (CV)	-	0.53
Name	**Pronation-Supination UPDRS task**		
	Meaning	***Unit***	***ρ-value***
X_1	Maximum supination (mean)	deg	-0.36
X_2	Maximum supination (CV)	-	0.05
X_9	Maximum supination velocity (mean)	deg/s	-0.42
X_{10}	Maximum supination velocity (CV)	-	0.35
X_{11}	Maximum pronation velocity (mean)	deg/s	-0.46
X_{12}	Maximum pronation velocity (CV)	-	0.44
X_{13}	Main Frequency	Hz	-0.47
X_{19}	Pronation Phase Duration	s	0.33

Legend
Coefficient of Variation: ratio of standard deviation (σ) to mean μ of the parameter. CV = σ/μ
Maximum Opening/Supination: peak of distance/angle in one movement
Amplitude: difference between maximum and minimum distance/angles in one movement
Duration: time elapsed between the start and the end of one movement
Maximum Opening/Supination Velocity: peak in an opening/supination phase of one movement
Maximum Closing/Pronation Velocity: peak in a closing/pronation phase of one movement
Opening/Supination Phase Duration: Time for opening/supination phase of one movement
Closing/Pronation Phase Duration: Time for closing/pronation phase of one movement
Rate: Number of movements per second
Main Frequency: Frequency with the peak in power spectrum (bandwidth 0.. 4 Hz)

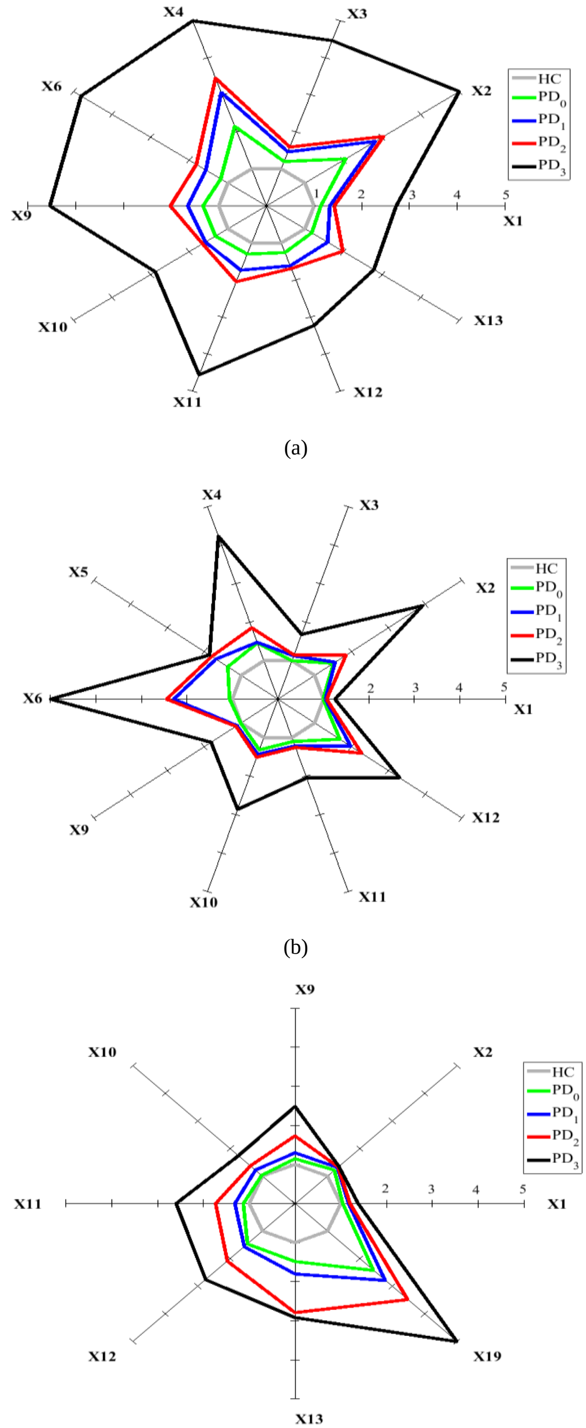

Figure 4. Radar graph from selected kinematic parameters for FT task (a), OC task (b) and PS task (c)

The probabilistic assignment **P** of the classifier output allows for an interesting extension to continuous values of the discrete UPDRS classification obtained using the most probable class. For this purpose, for each task, the probabilities **p**i to belong to specific UPDRS classes (i.e., the outputs of the related classifier) have been combined in a weighted mean.

In this way, a continuous estimation (W) of the UPDRS score is obtained (1):

$$W = \sum i \cdot p_i \qquad (1)$$

i = 0..4; p_i = probability to belong to class C_i

The advantage of this approach is the possibility to assess continuous variations of motor impairments that is not possible to obtain with a quantized (0-4) UPDRS score. A support to the correctness of the proposed extension is based on the choice of kinematic parameters, which are closely related to the clinical ones; the increase of a parameter value should correspond to an increasing of the neurologist's score. In practice, the classifiers output probabilistic assignment vectors **P** with only two significant probabilities that are related to contiguous classes. An application of the continuous UPDRS score estimate W in monitoring small fluctuation of patient impairment is presented in the preliminary experiments paragraph.

III. RESULTS

A. *Accuracy of the Automatic Assessment*

The confusion matrices shown in Table II, III and IV were used to characterize the classification performance of the SVM classifiers for the FT, OC and PS UPDRS tasks, both for the left and the right hand.

From them, all standard parameters for classifier evaluation (accuracy, sensitivity and so on) can be easily derived.

TABLE I. FT CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C_0	***C_1***	***C_2***	***C_3***
CLINICAL SCORES	C_0	15	3	0	0
	C_1	2	21	2	0
	C_2	0	1	18	3
	C_3	0	0	2	13

TABLE II. OC CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C_0	***C_1***	***C_2***	***C_3***
CLINICAL SCORES	C_0	14	2	0	0
	C_1	1	17	2	0
	C_2	0	1	22	3
	C_3	0	0	4	14

TABLE III. PS CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C_0	***C_1***	***C_2***	***C_3***
CLINICAL SCORES	C_0	8	3	0	0
	C_1	1	10	2	0
	C_2	0	2	30	6
	C_3	0	0	3	15

It can be noted the nonzero off diagonal elements of the matrices are one position far from the diagonal ones, meaning the classification errors were limited to one UPDRS class.

B. *Preliminary Experiments on UPDRS Assessment*

A preliminary experiment to assess the feasibility of the proposed system in monitoring PD patient at home has been conducted. A small group of PD patients (4 subjects) used the system at home for a period of a week. The subjects were instructed to perform FT, OC and PS task at different times (30m, 1.5h, 2.5h, 3.5h) from drug intake, every day of the week. The intent was to assess the potential fluctuations in upper limb motor performance in the period after the drug intake.

To give insight of the experiment results, a sample of the FT assessment is shown in Figure 5 for a PD patient, male, 65 years old, diagnosis at 60, non-fluctuating, and with more motor impairment on the right side. The patient was performing the upper limb UPDRS tasks daily, at different times (30m, 1.5h, 2.5h, 3.5h) from drug intake as required. Thanks to the data storage and the remote retrieving capability of the system, the session data (video, scores, parameters) and in particular the videos acquired by the system during task executions were accessed from remote, analysed and scored by the neurologist for both hands, resulting in a FT score of UPDRS 0 or UPDRS 1.

As shown in Figure 5, on the average, there is a good agreement between system and neurologist scores. Nevertheless, the system can assess tasks on a continuous scale (W score definition) respect to the standard discrete UPDRS score. This feature could open the possibility to investigate the interaction between drugs and motor effects with a more objective, sensible and hopefully accurate approach.

IV. CONCLUSIONS AND FUTURE WORKS

This work presents a non-invasive and low-cost system for the automatic assessment of PD patients performing standard upper limbs UPDRS tasks at home. The system is based on a new human computer interface that, by an accurate hand tracking allows both the system management and the automatic and objective UPDRS assessment. The hand gestural interface makes it suitable for motor impaired users, as are PD patients. The automatic assessment of UPDRS tasks is performed by a machine learning approach which uses some selected kinematic parameters that characterize the patient's movements. UPDRS task

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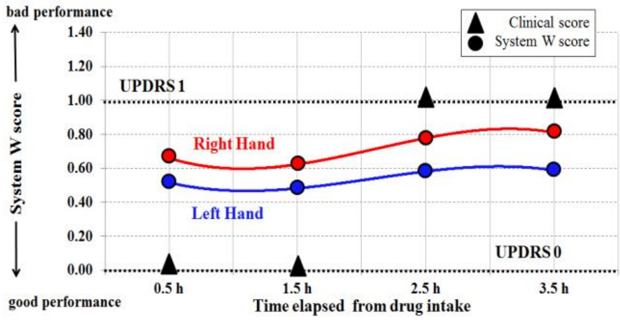

Figure 5. Automatic assessment of a FT task (left and right hand) at different times from drug intake. The continuous UPDRS assessment values and neurologist scores are shown at four different time. To facilitate the interpretation, scores are connected by coloured lines

classifiers were trained during an experimental campaign where PD patients were assessed by the neurologist and the system. The results about the obtained confusion matrices of the classifiers show the classification errors are limited to one UPDRS class and only in a few cases, making the system suitable for at home self-administrated assessment of upper limb UPDRS tasks. Based on the classifier outputs, a new continuous estimation of the UPDRS score is introduced and its potential benefit discussed.

Preliminary results about the application of the continuous UPDRS score in the at home monitoring of PD patients are presented. Further experiments are still needed to validate both the system usability and accuracy in the home environment, and the usefulness of the continuous UPDRS score here introduced in monitoring fine motor impairment fluctuations. Next steps will address also the extension of this solution to the analysis of other UPDRS tasks, aiming to obtain a global and comprehensive assessment of the neuro motor status of PD patients. It would be very important in the perspective of an optimization of the drug therapy, so improving both the clinical management and the patient's quality of life. This would be even more relevant if the overall assessment could be carried out at the patient's home, whenever more frequent observations are needed to better evaluate worsening in motor symptoms.

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