Home-Based Automated Assessment of Upper Limb Motor Function in Parkinson's Disease

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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 (PD). 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 uses the kinematic parameters that characterize the patient movements, as input to trained classifiers, with the aim of automatically rating the UPDRS scores of the performance. The classifiers have been trained by an experimental campaign, where cohorts of PD patients were contemporary assessed by a neurologist and the system. Results on the accuracy of the system assessments, as compared to the neurologist's ones, are given, along with preliminary results on monitoring experiments at home. Details about the user interfaces of the system, specifically designed for home-monitoring, are provided. The clinimetric properties of the system and its usability have been evaluated and reported. The results confirm that the system is suitable for the remote monitoring of PD patients at-home.**

Keywords - Parkinson's disease; UPDRS assessment; RGB-D camera; human computer interface; tele-monitoring.

I. INTRODUCTION

This article is an extended version of the paper presented at the Fourth International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems, SPWID 2018, and in particular at the PARKTECHNO special track, where some studies on new technologies for people with Parkinson's Disease were presented [1]. Parkinson's Disease (PD) is a chronic neurodegenerative disease characterized by a progressive impairment in motor functions (e.g., bradykinesia) [2], with important negative impacts on the quality of life. The Unified Parkinson's Disease Rating Scale (UPDRS) [3] is an international evaluation scale, commonly used by neurologists to assess the severity of the disease, whose motor symptoms are the most important and characterizing aspect. Specifically, standardized motor tasks, described into the Section III of the UPDRS and dedicated to the motor examination, 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, from 0 (no impairment) to 4 (severe impairment).

The assessment process takes into account specific kinematic features of the movements (such as amplitude, speed, rhythm variations) and anomalies (such as hesitations, freezing, incomplete movements), which are qualitatively and subjectively evaluated by neurologists. On the other hand, a quantitative and objective assessment of these tasks is considered important to increase the reliability of the clinical assessment [4] and to support the disease management and the patient care. 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 [5][6]. This correlation is used in the automatic and objective assessment of UPDRS motor tasks by several technological approaches, including those based on optical devices and wearable inertial sensors [7][8].

Another aspect to be considered is that drug treatment of the PD symptoms is crucial to reduce the effects of the impairment in daily activities. Because of possible fluctuations in impairment, it would be desirable to adjust the therapy on a weekly basis, both for the best effectiveness of the therapy and to reduce the side and long-term effects [9]. 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 the UPDRS motor tasks.

The paper is organized as follows. The state of the art on the technological approaches adopted in the analysis of the upper limb movements during UPDRS tasks is presented in Section II. The methodological approach we propose for the accurate tracking of hand and fingers movement is described

in Section III. In the same section, the graphical user interfaces, the methods used to evaluate the system usability and the agreement between standard and system assessments are also described. In Section IV, we present the results on the kinematic parameters selection, the automatic classification of the motor performance and the usability of the system. Furthermore, preliminary data about the assessment of patient's performance at home are provided. Conclusions and future work are discussed in Section V.

II. STATE OF THE ART

Several solutions have been proposed for the characterization of upper limb movements during the execution of UPDRS tasks. Approaches based on wireless inertial measurement devices (such as accelerometers and gyroscopes) [9][10][11] and on resistive bending sensors [12] do not suffer of occlusion problems, but they are more uncomfortable for people with mobility difficulties compared to the optical approaches and, more importantly, their invasiveness can affect motor performance.

Recently, optical approaches have been proposed for the hand tracking and the automated assessment of the upper limb tasks of UPDRS, namely: Finger Tapping (FT), Opening-Closing (OC) and Pronation-Supination of the hand (PS). In particular, solutions have been developed based on RGB cameras [13], passive markers [14] and bare hand tracking by consumer depth sensing devices [15][16][17][18].

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 [19]. Nevertheless, accuracy is an important requirement to be considered for the reliability of kinematic parameters and the assessment of the motor performance. Furthermore, the short life of these devices and the related Software Development Kit (SDK) warns against solutions that are too dependent on proprietary hardware and software.

Along this line of research, we present a low-cost system for the home-based automated assessment of the three upper limb tasks of the UPDRS (i.e., FT, OC, PS). The system hardware is based on lightweight colored gloves, an RGB-Depth sensor and a monitor, while the software implements the 3D tracking of the hand trajectories, characterizes them by kinematic features and assesses the motor performance by Machine Learning algorithms (i.e., trained supervised classifiers). The software performs the real-time tracking by fusion of both color 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 PD patients with motor impairments to self-manage the execution of the tests.

Respect to other approaches, based only on depth information and proprietary algorithms, the hand tracking is more robust and accurate for fast movements [19], making the final assessment more reliable. Another important characteristic of our solution is that it does not depend on any particular hardware or SDK; it assumes only the availability of RGB and depth streams at reasonable frame rate. Moreover, the accuracies obtained by the classifiers demonstrate the feasibility of the system in the remote assessment of the upper limb tasks of UPDRS. Some preliminary results are provided on the home monitoring of PD patients.

This version extends the conference paper providing more details about the natural user interface, specifically developed to allow patients the self-management of the tasks execution and the interaction with the system. The main features of the supervising component of the monitoring platform, designed to analyze the patient performance remotely, are presented. Finally, considering the importance of the usability aspects of a technology, results of a Post-Study System Usability Questionnaire (PSSUQ) are also presented.

III. 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 user's hand and finger movements. The user equipment consists of black lightweight gloves with imprinted color markers: each color marker corresponds to a particular part of hand to be tracked (e.g., fingertips and wrist) or to be used for color calibration and system interaction (e.g., palm). The working volume of the system is a pyramid trunk, which extends from 0.5m up to 2m from the RGB-Depth sensor. This guarantees enough space to perform the exercises comfortably.

The device drivers and our developed software are used to implement both the hand/fingers tracking and the HCI

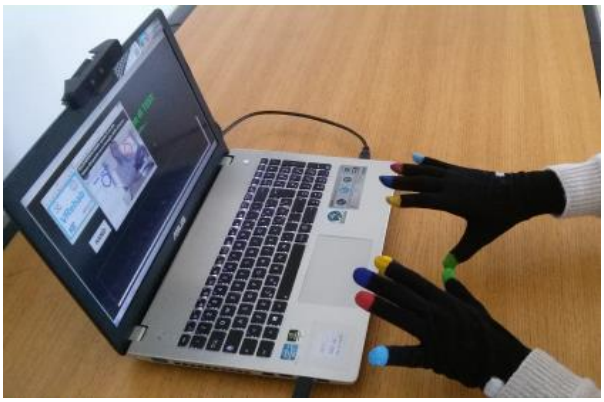


Figure 1. Hand/fingers tracking system

user interface. The software running on the PC implements the acquisition and processing of the data streams 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 the performance, extracted kinematic parameters and system scores are automatically encrypted and archived for further analysis and for clinician supervision and independent assessment.

B. Human Computer Interface for System Management

The software for the real-time hand/fingers tracking and the graphical user interfaces support the human computer interaction, thanks to which the patient can manage the test session (e.g., start and end the session, select a specific task, enter information on the perceived health status, etc.). Simple gestures, such as opening and closing the hand or pointing the fingers toward the interactive objects of the graphic menu displayed on the monitor, trigger specific actions.

The hand tracking software requires an initial setup phase, which consists of the global adjustment of the image brightness, the detection of the hand area and the color calibration for marker recognition and segmentation. The Intel LibRealSense library is used for the acquisition of RGB and Depth streams, while the OpenCV library [20] is used to retrieve the 3D position of the hand centroid from the Depth stream. A shaking movement of the user's hand 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 color and depth images. Then, the RGB stream is converted to the HSV color space, more robust to brightness variations.

The design of the color markers and the implementation of a color constancy algorithm compensate for the different lighting conditions that could be 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 white marker area are used to compensate for the predominant chromatic components due to the different types of lighting. Their values are used to scale each of the three HSV video sub-streams during the tracking phase.

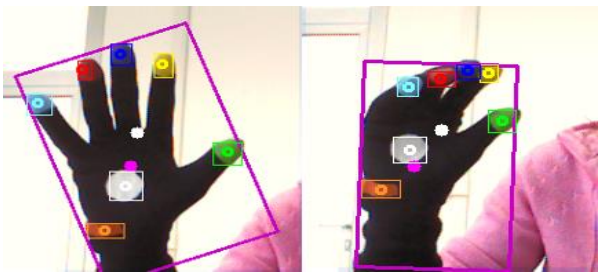


Figure 2. Hand segmentation and marker detection: color blob centroids and bounding box

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 color thresholds, selected during the initial setup phase, are used to detect and track all the color blobs of the markers. To improve performance and robustness, the CamShift algorithm [20] has been used in the tracking procedure. The 2D pixels of the area of every color marker are reprojected to the corresponding 3D points by standard reprojection algorithms to evaluate the 3D centroid of each color blob. Each centroid is an estimate of the 3D position of the corresponding part of the hand.

The trajectories of all centroids characterize the movements of the hand, which are used to evaluate the task performance (Subsection F).

C. Graphical User Interfaces of the system

The graphical user interfaces (GUIs) of the system become active automatically a few seconds after the system is switched on. The GUIs support two different functionalities, depending on the type of user. The patient GUI is displayed on the monitor at home, and provides the user with visual feedback concerning the movement of the hand and fingers, the actions triggered, and the input given (Figure 3). The GUI menus of the patient interface are managed only by hand gestures, allowing to start/end the session and to select the task to be performed, confirming the choice by closing the hand. Furthermore, the predefined menu items allow the input of some basic information concerning the patient's perceived condition and the type and dosage of drug taken.

Textual messages support the subject during the entire test session and the interaction with the system; in addition, a video guide can be activated by dedicated menu items if the patient has doubts on the correct execution of the task.

Regarding the clinician subsystem, the GUI provides the clinical management and the remote supervision of the patients. The GUI is designed for technical users without disabilities, and consists of a more complex structure, widgets and functionalities. In this case, the GUI input is provided by mouse and keyboard. The GUI is organized as a hierarchy of windows activated by visual objects that trigger the execution of specific actions. Preliminary authentication,

Figure 3. Human computer interface with natural gesture-based interaction of patient subsystem: example of GUI for the task selection

via personal credentials, guarantees a secure access to data only to authorized clinicians.

The main window GUI (Figure 4) allows to select the patient's folder from a repository in which videos, kinematic parameters and system scores of each performance were stored. The clinician can select a particular performance recorded among all those archived; then videos, reports with automated scores and information entered by the patient are displayed to be analyzed by the neurologist. Each video is managed by the functions of a standard video player object (start/stop/pause, rewind, slow motion, etc.), which allows a detailed analysis of the patient's performance. In the lower area of the main window, the clinician can add useful annotations to the record, including the clinical assessments. This information is then stored as part of the patient's record. Messages or communications to patient can be written by the clinician into the dedicated "MSG TO PATIENT" box to be displayed on the main GUI of the patient subsystem before starting the next session. From the main window GUI, four other child windows can be opened.

The first child window (Figure 5), activated from the menu bar of the main window, provides a GUI that is intended to analyze and compare the performances, for the different upper limb tasks, of the left and right hand in the same acquisition session. In the graph area, the radar plots generated by the kinematic parameters of the left and right hand performances are displayed. The average values of the parameters for the UPDRS 0 class (green line), which are estimated from the reference database as described in Subsection D, are also displayed. They are used as reference values for a quick visual comparison of the patient's performance. The UPDRS class and the continuous score W, estimated by the system for each performance, are displayed in the right area of the window.

The second child window (Figure 6) provides a GUI that is intended to analyze and compare the performances, for each motor task, of the left and right hand but in different acquisition sessions. This GUI aims to monitor the evolution over time of the kinematic parameters that characterize the motor performance.

Figure 4. The main window GUI for the clinician subsystem.

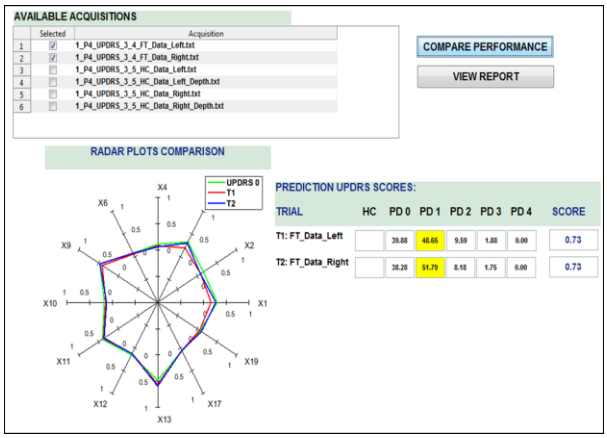


Figure 5. GUI used to compare performance of the left and right hand and to detect asymmetries. The automatic and continuous scores are displayed for each performance.

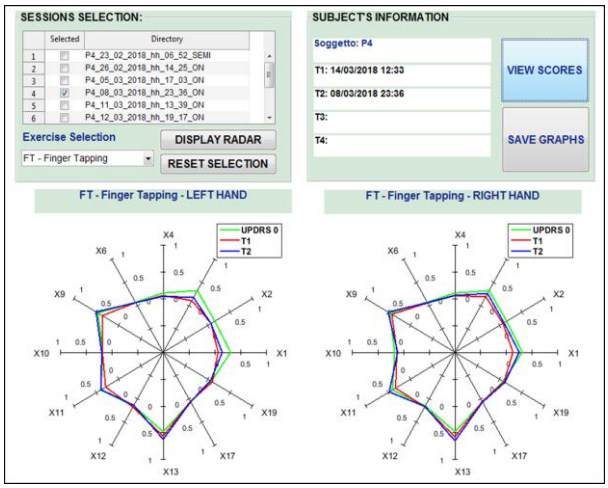


Figure 6. GUI used to compare and highlight the evolution of the performance for the left and right hand over time.

Up to four sessions can be displayed simultaneously; the related parameters can be compared immediately each other and respect to the reference parameters relating to the UPDRS 0 class. The "VIEW SCORES" button, in the upper area of the GUI, opens a third child window GUI (Figure 7). This window displays the prediction of the UPDRS classes (i.e., the output probabilities estimated by the supervised classifiers) and the continuous score W computed by the system for each performance, allowing for an easy comparison of the evolution of the patient impairment.

Finally, from the menu bar of the main window GUI, a fourth child window can be opened (Figure 8). This window allows to monitor the evolutionary trend of each kinematic parameter over time. The information displayed here may be useful to detect specific motor patterns hidden in similar performance scores, highlighting any changes in behavior over time and for both hands.

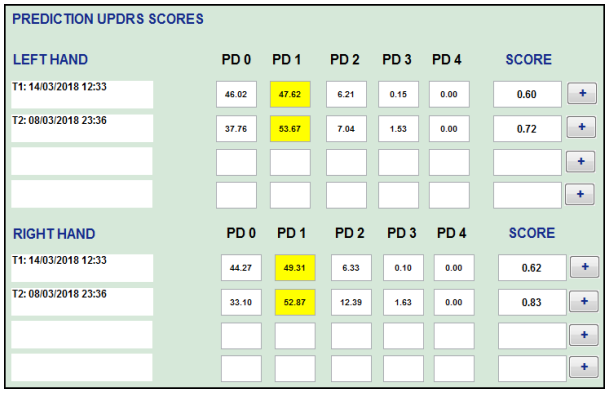


Figure 7. GUI used to display the automatic prediction and scores (output of the SVM classifier) for the selected trials, to quantify the evolution of the motor performance over time.

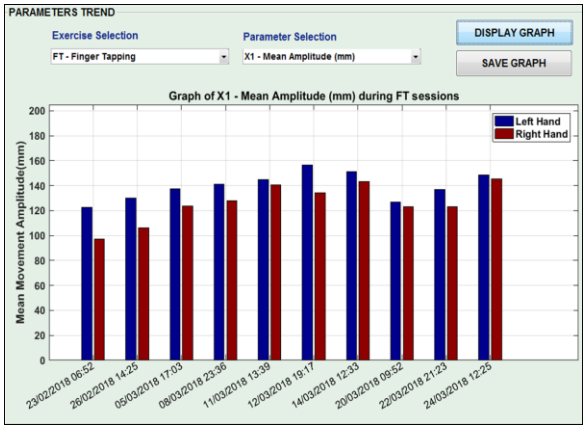


Figure 8. GUI used to display the trend of a single kinematic parameter, highlighting any change in behavior over time and for both hands.

D. Clinical Assessment and Data Acquisition

An experimental campaign was carried out to collect the kinematic data and the neurologist scores on the performances of a group of PD patients while performing the upper limb UPDRS tasks, that is Finger Tapping (FT), Opening-Closing (OC) and Pronation-Supination (PS). The goal was both to select the kinematic parameters that best characterize the differences in the impairment severity, and to collect a database of "kinematic parameters vector – neurologist UPDRS score" pairs to train the supervised classifiers of the system used for the automated assessment of each task. Two cohorts were recruited: one composed of forty patients (22 females, 18 males) with a diagnosis of Parkinson's Disease (PD), and the other composed 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.

PD subjects were excluded if they had previous neurosurgical procedures, tremor severity > 1 (UPDRS-III severity score), or cognitive impairment (Mini–Mental State Examination 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 a neurologist experienced in movement disorders and the resulting UPDRS severity scores were found between 0 (normal) and 3 (moderate impaired). Every performance of the PD patients was tracked by the system and the related kinematic parameters were automatically extracted from the hand/fingers trajectories. The HC subjects performed the tests under the same environmental conditions and with the same system configuration as the PD patients. Before starting the acquisition campaign, a meeting was conducted to train the neurologist, staff and PD participants in the use of the system and to get acquainted with the procedures to be followed during the data acquisition.

E. Validation of the agreement between neurologist and system assessments

The goal of this work is the development of a telemedicine approach for the home-based assessment of Parkinson's Disease.

In this context, it is important to verify the agreement between the neurologist and the system assessments, both during the acquisition of experimental data and during the remote supervision, when videos of the patient performance are supervised and eventually assessed by neurologists.

The agreement between system and neurologist has been addressed using the Intra Class Correlation (ICC) coefficient [21]. The $ICC_{N\text{-}SY}$ coefficient, between the live scores assigned to each task by the neurologist and the system at the end of the patient's performance, was evaluated by applying the two-way random effects model for absolute agreement.

In addition, to verify if the video of the performance conveys enough clinical information for the remote supervision, the $ICC_{N\text{-}V}$ between live and video-based assessments was also evaluated, this by applying the two-way mixed effects model for absolute agreement.

F. Kinematic Parameter Selection

The automatic assessment of UPDRS tasks makes use of the well-established 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 [5].

The kinematic parameters we choose are closely related to the typical characteristics of the patient's movements that are used by neurologists to score the performance (amplitude, speed, rhythm, hesitations, and others). To compact the information associated with these parameters and to reduce their redundancy, the most discriminant ones

have been identified for every UPDRS task. First, the Principal Component Analysis (PCA) has been applied to the initial set of parameters to filter out those that contribute less than 5% to represent the whole dataset. Then, the selected kinematic parameters were correlated to neurologist's UPDRS scores (Spearman's correlation coefficient ρ), keeping only those with the best correlation with neurologist's UPDRS scores, at significance level $p<0.01$.

In this context, the kinematic parameters of the HC subjects have been used to normalize the PD ones. Thanks to the better performance of the 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 the set of normalized PD parameters ($\mathbf{p}_{i\,PD\,norm} = \mathbf{p}_{i\,PD} / \mathbf{p}_{i\,HC}$).

G. Automatic UPDRS Assessment by Machine Learning

To implement the automatic assessment of the FT, OC and PS UPDRS tasks, three data sets of "kinematic parameters vector – neurologist UPDRS score" pairs were used to train three different classifiers. We use the LIBSVM library package [22] to implement three Support Vector Machine (SVM) classifiers with polynomial kernel. Their accuracy in the correct assignment of 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 each SVM classifier.

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

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 output of the classifier) have been combined by a weighted average. In this way, a continuous estimation W of the UPDRS score is obtained:

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

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

The advantage of this approach is the possibility of evaluating continuous and slight variations in motor impairment that is not possible to obtain with the standard quantized UPDRS score (0-4). In practice, the classifiers estimate probabilistic assignment vectors **P** having only two significant components that correspond to contiguous classes. An application to the monitoring of small fluctuations in patient impairment by the continuous UPDRS score, estimated through W, is presented in the paragraph of preliminary experiments.

H. Clinimetric validation and usability of the patient subsystem

Clinimetric validation was considered successful if a health monitoring system is shown to be reliable, valid and sensitive to changes [23][24][25]. Reliability is defined as the degree to which the measure is error-free and, consequently, produces consistent results. We use the Intra Class Coefficient (ICC) as a measure of reliability. Validity is the degree to which an instrument measures the construct it purports to measure, and we assess the system validity by the accuracy of the automated assessments as compared to the neurologist ones (Subsection C of the Results). Sensitivity is related to the ability of the system to detect changes over time. We evaluated the sensitivity in a preliminary longitudinal experiment by monitoring a limited number of PD subjects at home over a week (Subsection D of the Results). We use the continuous estimation W of the UPDRS score as defined in Equation (1) to assess the sensitivity to small changes in motor impairment.

In addition to clinimetric validation, other important aspects that a home-based and self-administered health monitoring system should show are a good usability and acceptability. For this purpose, all the recruited PD patients were interviewed at the end of their respective sessions to evaluate their global level in computer and technological skills, their ability to wear gloves, and their satisfaction in using the system. The interview was conducted by presenting them a set of adjectives qualifications referring to the system.

Furthermore, the system usability was assessed by the standardized interview of the Post-Study System Usability Questionnaire (PSSUQ) [26]. This is a 19-items ordinal score questionnaire based on 7-point Likert scales, which addresses six components of user satisfaction with regards to the systems usability: ease of use, ease of learning, simplicity, effectiveness, information and user interface.

The users' computer and technological skills were evaluated by their dichotomous answers (yes/no) to a questionnaire of 18 items concerning the previous use of information technologies (IT), the difficulties encountered in using the system, the need for a supervisor and the comprehension of the sequence of activities to be performed during the session. The users' responses to the proposed items have been added in a final score divided into 4 IT skill levels (i.e., none, basic, intermediate, advanced). The ability to wear gloves was evaluated by the session supervisor on three levels (i.e., impossible to wear, wearable with aid, wearable without aid).

The satisfaction in the use of the system was assessed by showing to the subject the image in Figure 9 at the end of the session, asking him/her to choose the three adjectives that best qualify the experience. Once again, the answers were added over all the subjects to obtain the three most important adjectives chosen by the PD cohort. The PSSUQ makes use of a standardized set of questions and procedures to evaluate the usability of the system [26].

Figure 9. Imagine shown to the users at the end of the session, with the set of proposed adjectives to qualify the experience in using the system.

IV. RESULTS

A. Discriminant kinematic parameters

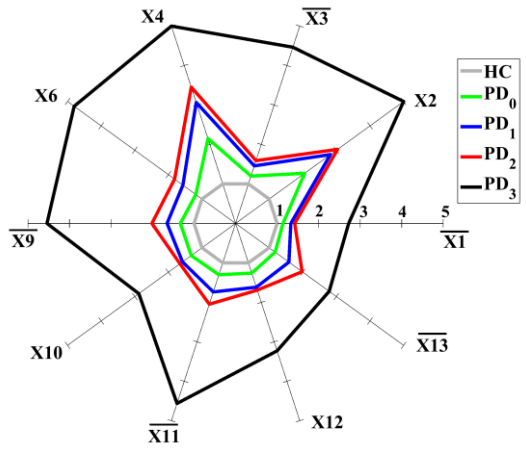
The parameter selection process, applied to the initial set of normalized parameters, produces three sets of discriminant parameters (Table I) that are able to discriminate the UPDRS classes for the FT, OC and PS tasks, respectively. This is confirmed visually by the average values of the kinematic parameters selected with respect to the UPDRS severity classes, as shown in the radar graphs of Figure 10(a) for FT, Figure 10(b) for OC and Figure 10(c) for PS tasks, respectively.

In Figure 10, the increase of the motor performance severity corresponds to an expansion of the relative radar graph. Note that, to highlight the discriminant power of the selected parameters, they have been represented directly (with the name of the original parameter) or inversely (with an overscore on the name of the original parameter), depending on whether the parameter value increases or decreases when the severity of the impairment increases. Furthermore, for graphical representation purposes, the parameters are scaled, so that the values corresponding to the best performance ($\mathbf{p}_{i\ PD\ no} = \mathbf{p}_{i\ HC}$) are represented on the innermost circle (i.e., radius value = 1).

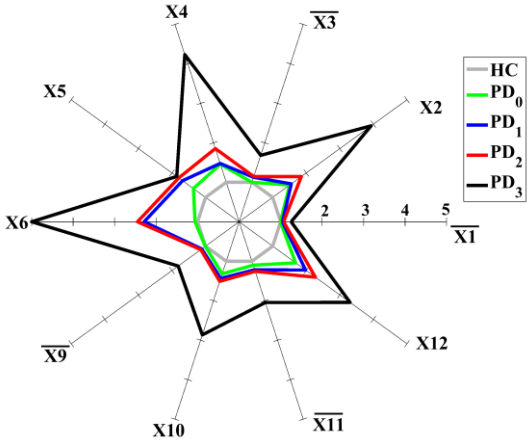
TABLE I. SELECTED KINEMATIC PARAMETERS

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

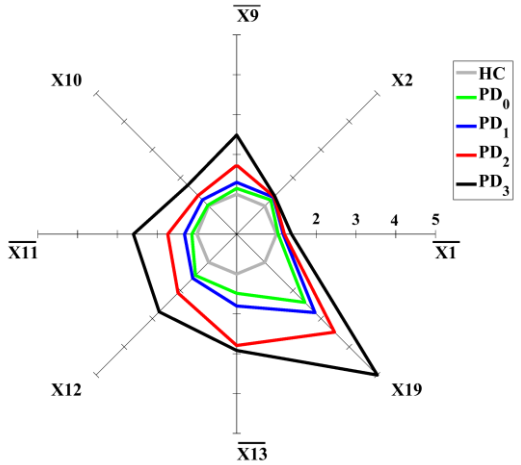
Legend
Coefficient of Variation: ratio of standard deviation (σ) to mean μ of the parameter. CV = σ/μ
Maximum Opening/Supination: peak of distance/angle in one movement
Amplitude: difference between maximum and minimum distance/angles in one movement
Duration: time elapsed between the start and the end 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)



(a)



(b)



(c)

Figure 10. Radar graph of selected kinematic parameters for FT task (a), OC task (b) and PS task (c)

B. *Accuracy of the Automatic Assessment*

The confusion matrices, shown in Tables 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 the confusion matrices, all the standard parameters for the evaluation of the classifier performance (such as accuracy, sensitivity and so on) can be easily obtained.

It can be noted that the non-zero elements outside the diagonal of the matrices are only one position far from the diagonal ones, which means that the classification errors are limited to one UPDRS class.

TABLE II. FT CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C₀	***C₁***	***C₂***	***C₃***
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 III. OC CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C₀	***C₁***	***C₂***	***C₃***
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 IV. PS CONFUSION MATRIX (UPDRS CLASSES)

		SYSTEM SCORES			
		C₀	***C₁***	***C₂***	***C₃***
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

C. *Usability assessment of the system*

The percentage breakdown of the computer skills of the PD users for none, basic, intermediate and advanced levels, is 55.2%, 18.0%, 16.8%, 10.0%, respectively. Most PD users (over 73%) had no or low computer skills, making the test representative of an elderly population of PD subjects.

The percentage breakdown of the ability to wear gloves for the three levels (i.e., impossible to wear, wearable with aids, wearable without aids) is 3%, 5%, 92%. This result

confirms that the system is quite user-friendly for people with motor impairment as PD subjects and gloves are not such an invasive equipment.

Concerning the adjectives chosen as representative of the experience with the system, the most voted ones are interesting (56%), helpful (50%), exciting (44%), stimulating (38%), unusual (25%), improvable (25%). Moreover, all the adjectives chosen have a positive meaning for the acceptability of the system. The word cloud of the characteristics expressed by the PD patients to describe their experience of using the system is shown in Figure 11. The word cloud (wordle) gives an intuitive indication of the relative importance of the adjectives proposed through the typical graphic style. The biggest words represent the most voted adjectives among the ones presented to the subjects during the interview at the end of the experimental session. Each subject was asked to selected three adjectives from a set of "positive" and "negative" words, giving us a direct feedback on the most and the least features voted in terms of usability, satisfaction and acceptability of the system.

Figure 12 shows the results of the PSSUQ questionnaire on the usability of the system, mediated on the PD cohort. Subjects were asked to answer 19 questions on the system by assigning a Likert score (1 absolute agreement, 7 absolute disagreement) to express their standard positive or negative judgement on the experience of using the system [26]. The 19 items are ordered from the first question (on the left) to the last one (on the right); for each question, the average score is reported. The analysis shows that the PD participants rated the usability of the system with an overall average score of 2.16 (±0.58) on the PSSUQ. This indicates that the majority of participants liked to use the system and appreciated the possibility offered by the system to monitor their own health condition at home.

Figure 11. The word cloud of the most voted characteristics indicated by the cohort of PD patients to describe their experience in the use of the system.

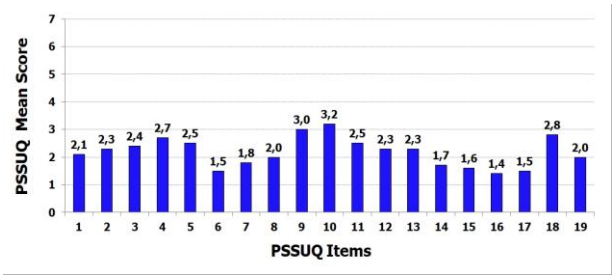


Figure 12. Results of the PSSUQ questionnaire on the usability of the system.

D. *Preliminary Experiments on UPDRS Assessment*

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

Thanks to the data storage and the remote retrieving capability of the system, the test session data such as scores, parameters and, in particular, videos captured during the task execution, were remotely accessed, analyzed and evaluated by the neurologist for both the hands.

In this experiment, the agreement between the automatic scores of the system and the video-based scores of the neurologist has been evaluated by the ICC coefficient (two-way random effects model for absolute agreement). The ICC values have been evaluated for each task, collecting the four daily scores for the entire week, this for all patients. In Table V, the resulting ICC coefficients for the tasks are shown.

To give insight of the experiment results, in Figures 13, 14, and 15 are shown samples of the daily assessments by the system and by the neurologist for the FT, OC and PS tasks on the performance of a PD patient. This patient is a 65-year-old male, diagnosed for PD at 60, non-fluctuating, and with more severe motor impairment on the right side.

TABLE V. INTRA CLASS CORRELATIONS FOR THE AGREEMENT BETWEEN NEUROLOGIST AND SYSTEM SCORES

	UPDRS task		
	FT	**OC**	**PS**
ICC_{NV-SY}	0.80	0.61	0.58

The ICC values of the neurologist-system agreement for the three UPDRS tasks. The neurologist assessments are based on the recorded videos of the performances of the four patients.

The neurologist's scores are based on the recorded videos of the patient's performances: scores are evaluated and shown at four different times per day. To facilitate the interpretation, system scores expressed as continuous values W are connected by solid colored lines (red for the right hand and blue for the left hand, respectively).

In Figure 14, the large difference between left and right hand scores for the OC task, occurring at 2.5 hours from drug intake, could be due to the subjective evaluation of the neurologist. This hypothesis is supported by the other performance scores of the neurologist for the FT and PS tasks at the same time, which show less differences between the two hands. The system scores are less fluctuating, compensating for possible incorrect subjective evaluations.

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

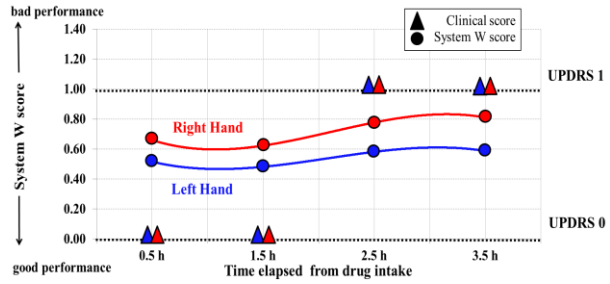


Figure 13. Example of the automatic assessment of the FT task for the left (blue) and right (red) hand at different times from drug intake. The continuous assessment scores (System W score) by the system and the standard UPDRS scores (Clinical score) by neurologist are shown at four different time. To facilitate the interpretation, system scores are also connected by solid lines.

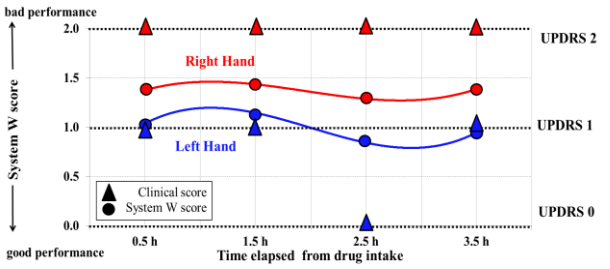


Figure 14. Example of the automatic assessment of the OC task for the left (blue) and right (red) hand at different times from drug intake. The continuous assessment scores (System W score) by the system and the standard UPDRS scores (Clinical score) by neurologist are shown at four different time. To facilitate the interpretation, system scores are also connected by solid lines.

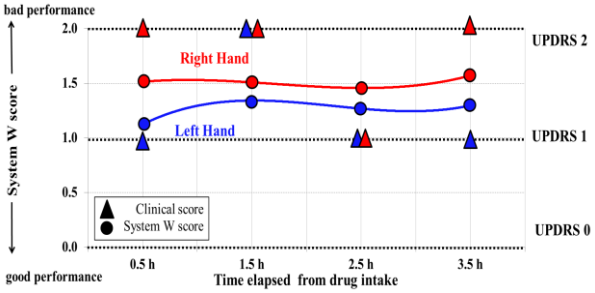


Figure 15. Example of the automatic assessment of the PS task for the left (blue) and right (red) hand at different times from drug intake. The continuous assessment scores (System W score) by the system and the standard UPDRS scores (Clinical score) by neurologist are shown at four different time. To facilitate the interpretation, system scores are also connected by solid lines.

V. CONCLUSIONS AND FUTURE WORKS

This work presents a non-invasive and low-cost system for the automatic assessment of subjects with PD that perform standard UPDRS tasks for upper limbs at home. The system is based on a new human computer interface that, through the accurate hand tracking, allows both the management of the system and the automatic and objective UPDRS assessment.

The gestural interface makes it suitable for users with motor impairment, as are PD patients. The user interface of the system has been specifically designed for the home monitoring of people with mobility difficulties, as those affected by Parkinson's Disease.

The system interface of the remote supervisor provides a secure access to the clinical data. Furthermore, all relevant clinical data (videos, reports with automatic scores and information entered by the patient) are displayed and can be easily analyzed by the clinician. Textual messaging can be used by the remote supervisor to send messages, which are shown on the GUI of the patient subsystem at the start of the next acquisition session.

The automatic assessment of UPDRS tasks is performed by a machine learning approach that uses some selected kinematic parameters that characterize the patient's movements. The classifiers, one for each UPDRS task, were trained during an experimental campaign in which patients with PD were assessed at the same time by the neurologist and the system. The results obtained from the classifiers confusion matrices show that classification errors are limited to one UPDRS class and only in some cases, making the system suitable for the self-managed assessment of the upper limbs UPDRS tasks at home. Based on the classifier output, a new continuous estimate of the UPDRS score is introduced and its potential benefit is discussed.

The clinimetric properties of the system and its usability for PD users have been evaluated. The results confirm that the system is suitable for the monitoring of Parkinson's Disease at-home.

Preliminary results on the application of the continuous UPDRS score in the at home monitoring of patients with PD are presented. Further experiments are still needed to validate both the usability and accuracy of the system in home environment, and the usefulness of the continuous UPDRS score introduced here for monitoring fine fluctuations of motor impairment.

Next steps will also cover the extension of this solution to the analysis of other UPDRS tasks, with the aim of obtaining a complete and comprehensive assessment of the neuro-motor status of PD patients. This would be important in the perspective of the optimization of the drug therapy, because the assessments could be carried out on demand at the patient's home whenever more frequent observations are needed to assess the worsening of motor symptoms. All these features are relevant to significantly improve both the clinical management and the patient's quality of life.

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