A Preliminary Comparison between Traditional and Gamified Leg Agility Assessment in Parkinsonian Subjects

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***Abstract*—Parkinson's disease (PD) severity is assessed through a set of standardised tasks defined by clinical scales such as the Unified Parkinson's Disease Rating Scale (UPDRS). In particular, Leg Agility is a well-established test among the motor tasks included in UPDRS, which consists in repeated cycles of knee lifting and lowering, while sitting on a chair. Leg Agility objective evaluation through optical devices is often investigated for telemedicine applications. Moreover, remote rehabilitation for PD subjects through virtual exergaming is becoming a popular approach thanks to its versatility, increased user engagement and the possibility of coupling it with remote monitoring tools. This work investigates if lower-limb exergaming may also be exploited for assessment purposes similar to traditional evaluation. In particular, if there exists a statistical difference between the kinematic description of Leg Agility versus the one of a Bouncing Ball exergame, as provided by an optical (RGB-D) acquisition system suitable for remote monitoring. Preliminary results obtained by the comparison of the two types of assessment in a small group of parkinsonian subjects are presented and discussed.**

***Index Terms*—Exergame, Gamification, Parkinson's disease, Telemedicine, Leg Agility, Azure Kinect**

I. Introduction

Parkinson's disease (PD) is a chronic and disabling neurodegenerative disease characterised by motor dysfunctions that worsen along disease progression. Tremor, muscles stiffness (rigidity), bradykinesia, hypomimia, abnormal posture, gait and balance disorders are the most common among motor symptoms [1]. Unified Parkinson's Disease Rating Scale (UPDRS) is the most widely employed scale in clinic to assess impairment severity for PD, through a set of standardised tasks [2]. In particular, section III of the UPDRS focuses on motor examination and includes 18 items that aim to establish the impairment severity on different motor functions. Neurologists usually conduct the motor examination during scheduled follow-up visits in clinical settings; each item is scored on the basis of the observed motor performance and the perceived abnormalities during the task execution. The assessment is thus affected by intersubject variability between the clinicians in charge of evaluating the test [3].

A quantitative evaluation of UPDRS motor tasks through automatically-extracted objective features would be of great interest; indeed, it could help clinicians to modulate therapies and define personalised rehabilitation protocols according to actual needs, thus reducing the long-term complications and lower efficacy of non-optimised treatments [4] [5]. In addition, it could be the basis for developing integrated home-based solutions that combine the assessment of standard motor tasks and exergames for rehabilitation, thus enhancing the remote patients' follow-up, reducing the discomfort of frequent access to clinical facilities, and extending the benefits of traditional physical and cognitive rehabilitation [6] [7] [8]. In the last decade, several studies proposed technological solutions to evaluate UPDRS motor tasks objectively and to analyse specific characteristics of human body movement in individuals with PD [9] [10].

More in general, the developed solutions adopt two different approaches: wearable sensors (including inertial sensors, accelerometers, and, more recently, smartphones) [11] and optical sensors (e.g. RGB-Depth cameras) [12]. In particular, several studies propose optical approaches to characterise and assess upper limb motor function [13], analyse dysfunctions in lower limbs and postural control [3], estimate gait features [14], evaluate arms swing [15], analyse balance disorders [16] [17]. Optical approaches are also widely used to design motor rehabilitation solutions for specific pathologies [18] [19], including Parkinson's disease [20], thanks to a generally recognised non-invasiveness, portability, versatility, high usability, and easy integration into virtual reality environments. For example, solutions based on optical sensors address the rehabilitation of lower [21] and upper limbs [22], balance disorders [23], cognitive and motor dysfunctions [24], and

Fig. 1. BB game screenshot

gait [20]. Serious games, also known as exergames, are a broadly investigated technique for a more stimulating and engaging motor-cognitive rehabilitation in healthcare [25], that have already proven their feasibility and usefulness in several studies. However, most of the studies about exergaming in PD focus on the rehabilitative nature of exergames, without considering them as an additional source of information about the patient current motor status [26]. In a remote monitoring scenario, it could be useful to *gamify* also the assessment stage, for several reasons: to produce objective and quantitative data; to increase patient engagement, motivation and satisfaction in performing the evaluation more frequently; to stimulate and evaluate specific motor aspects of the patient through goal-oriented movements.

This work focuses on the Leg Agility (LA) task of UPDRS motor examination and its gamification for assessment purposes. In particular, a gamified version is realised through a Bouncing Ball (BB) exergame. An RGB-D camera (Azure Kinect) is used for tracking human body movements during traditional LA and BB game trials by a small group of parkinsonian subjects. Some kinematic features of the collected body tracking data are computed and statistically compared to highlight alterations and similarities in the way subjects perform the same motor task in a traditional and in a gamified version. Preliminary results obtained on a small group composed of 15 PD patients are presented and discussed.

II. Materials & Methods

A. Leg Agility

The UPDRS motor tasks are a standardized examination method used in PD for assessing the patient's condition and progression, observing changes in the habitual motor behaviour or the most impairing effects of symptoms on motor performance. In particular, this work focuses on LA, which can be easily performed by subjects in unsupervised (home) settings thus it is suitable for remote monitoring.

LA is performed in a sitting position, by raising and stomping the foot on the ground at maximum velocity and performing the maximum excursion, for a specific number of repetitions (at least 10) or for a fixed time interval. The task is performed with the left and the right leg separately. Even though simple, LA is able to highlight typical motor symptoms such as bradykinesia, hypokinesia, muscle stiffness, fatigue, which affects control and coordination of leg movements during task execution.

B. The Bouncing Ball Exergame

Exergames in virtual environments aim to stimulate the motor functions through specific activities, such as stretching or mobilisation exercises, in a more engaging, motivating, and enjoyable way than traditional physical training. In order to investigate if such games could also be employed for motor assessment as an alternative (or complementary) tool to traditional analysis, a Bouncing Ball (BB) game mimicking movements from LA task is presented. The game is developed in Unity 2019, exploiting Azure Kinect body tracking algorithm to implement both Human Computer Interaction (HCI) and game logic.

BB relies on repetitive movements of the lower limbs to address motor control and coordination by promoting leg mobilisation. The exergame is set in an office scenario and consists of dribbling the ball with legs (thighs). The exercise is performed in the sitting position as during the traditional LA task. Fig. 1 shows a screenshot of the game visual environment displayed to the user during BB.

The exergame requires the user to perform a predefined number of leg lifting movements (LEGMOV) to hit the ball with the right and then with the left knee. The ball is highlighted by a halo when ready to be hit: the patient should wait for its turn-on before starting the movement. Time between consecutive ball turn-ons (TURNONTIME), hence the cadence of the task, can be modified, allowing for a more relaxed or more dynamic execution. The ball starting position is expressed as a percentage increase with respect to the knee rest position (BALLSTART). The 3D skeletal model reconstructed by Azure Kinect body tracking algorithm maps with the avatar's legs on the game scene: every time the subject raises his leg, the corresponding virtual leg of the avatar will also raise. When hit, the ball will bounce upward and then fall back to the starting position, with a velocity dependent on TURNONTIME. It is necessary to perform the expected number of movements within a maximum time (LEGMAXTIME) to complete the game: a real-time algorithm analyses the leg movements and counts the "good" movements, i.e., those that result in a ball hit. This information is shown to the user, who also receives a positive acoustic feedback when hitting the ball. The therapist pre-configures the game parameters (i.e., LEGMOV, BALLSTART, LEGMAXTIME, and TURNONTIME) according to the patient's motor condition, choosing among three possible levels for each parameter.

C. Acquisition & Processing system

The acquisition system employed both for LA and BB tasks consists of a few hardware components providing a simple, not bulky, and contactless solution for 3D motion capture. It is composed of a mini-computer, an Azure Kinect camera, and a monitor (or a TV screen) that is employed for visual and acoustic feedback in BB. Azure Kinect provides synchronised color, depth, and infrared streaming at approximately 30 frames per second, thus allowing the real-time tracking of human body movements. Screen size (27” monitor) and Graphical User Interface (GUI) layout of BB were chosen to address reduced sight typical of elderly. The system ability in evaluating UPDRS tasks in agreement with standard clinical scores has already been verified in several studies, as well as the accuracy and robustness of the tracking algorithm compared to optoelectronic tracking systems [3] [27]. The software running on the mini-computer mainly relies on the body tracking algorithm provided by the Software Development Kit (SDK) of Azure Kinect camera. The estimated 3D joints of the skeletal model allow the interaction with the avatar and with the game environment through natural body movements in BB and the evaluation in post-processing of the motor performance both in LA and in BB recordings.

The system includes a specific procedure to store all the data related to the skeletal model as a file in JSON format: such output consists of a complex structure that contains 3D position and rotation of each body joint, tracking confidence and timestamp. This information is used to extract some kinematic features characterising the motor performance during the post-processing phase, as described in section II(D), through custom written MATLAB 2020b scripts.

D. Recruited Subjects and Acquisition Protocol

The experimental protocol fixed some exclusion criteria that include severe disability, severe and almost continuous tremor with inadequate response to therapy, cognitive impairment (Mini–Mental State Examination Score $<$ 27/30), and severe visual impairment. We expect patients with moderate disability (Hohen-Yahr scale, H-Y $\leq$ 3) to benefit from the proposed solution, as monitoring the motor fluctuations and the motivational engagement in rehabilitation become relevant at this stage. For this study, 15 PD subjects (H-Y: 2.3 ± 0.7 (min:1; max: 3); average age: 67.8 ± 10.13; gender: 7M/8F) were recruited for the experimental test at the Division of Neurology and Neurorehabilitation, San Giuseppe Hospital, Istituto Auxologico Italiano, Piancavallo (Verbania), Italy. The local ethics committee approved the study according to the Helsinki declaration (1964) and its amendments. Finally, all participants were volunteers, provided written informed consent prior to participating in the experimental session, and performed the test under the same conditions.

Subjects were assisted during experiment by technical personnel, which was also responsible to instruct them about the task to perform in each stage. The acquisition protocol consisted in first executing LA for ten seconds (for each leg), then playing BB (left leg, then right leg) and finally executing again LA for other ten seconds (for each leg). During LA, the subject performed the task in front of the Azure Kinect without any visual or acoustic feedback from the acquisition system, as in a normal clinical evaluation. Start and stop of the task were controlled by technical personnel. During BB, visual and acoustic feedback was provided through an off-the-shelf monitor positioned behind the camera. Considering each leg trial as single, a total of 60 LA and 30 BB trials were collected. In terms of pure leg-raise segments (movements), 737 and 112 segments were identified and analysed for LA and BB respectively.

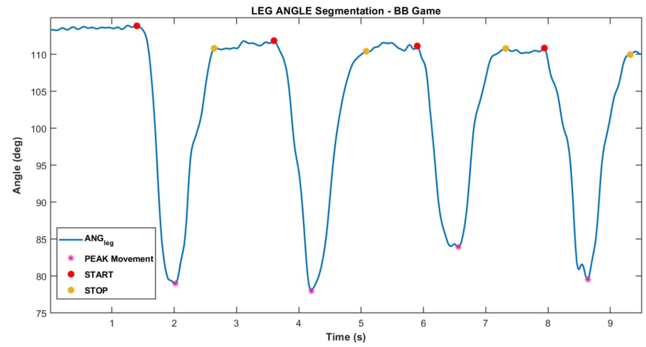

Fig. 2. ANG_{leg} and its segmentation in a BB trial

E. Kinematic Features Estimation

From the JSON files containing the time evolution of the skeleton during the single task execution (both LA and BB and for each leg), some relevant joints (i.e, SPINE NAVAL, PELVIS, KNEE, HIP and ANKLE of the leg of interest) are taken into account. 3D joint trajectories are low pass filtered (8 Hz, suitable to capture human voluntary movements) and resampled at 50 Hz through linear interpolation. The angle between the segments HIP-KNEE and SPINE NAVAL-PELVIS (i.e., the angle between the trunk and the thigh, called ANG_{leg}) is calculated. ANG_{leg} decreases while the knee is lifting, an example of such angle from a BB trial is reported in Fig. 2. Kinematic features to objectively characterise the movement are extracted from KNEE and ANKLE trajectories and ANG_{leg}. The analysis is done both with parameters describing the entire task execution for one leg (task-level) and at the level of a single executed movement (segment-level).

At the task-level, global parameters of the recording are calculated. The focus is on describing the amplitude and velocity of the movement because these are among the most important features to be considered in LA clinical assessment, together with changing in timing and movement direction [28]. Therefore, the ANG_{leg} travelled (amplitude excursion) and the speed are considered as primary measurements of leg motion in LA and BB. A complete list of the estimated features is shown in Table I. In addition, the 3D trajectories of the KNEE and ANKLE joints are exploited to evaluate the swings in all directions occurred during the lifts and the regularity of the movement. An example of the trajectories followed by left KNEE and ANKLE during a LA execution with the left leg is shown in Fig. 3.

A regular execution is reflected in a trajectory that overlaps itself over time. The more such trajectory is extended along one direction, the less swing is present in the movements. Geometric considerations are used to translate these aspects

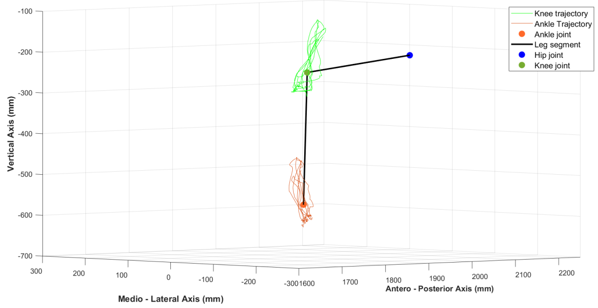

Fig. 3. 3D Trajectories of left ANKLE and KNEE in a LA trial (left leg moving)

into features. The areas of the 2D (Frontal and Transverse) planes and the volumes of 3D convex hulls in which the trajectory is inscribed are computed. In both cases, the higher the value of the parameter, the greater the irregularity of the track and the movement outside the main trajectory (the up and down of the knee). Moreover, to characterise the rhythm of execution, frequency features are computed. The frequency corresponding to the maximum spectral power, obtained from Fourier Transform, is considered as the main frequency. The frequency band containing the 90% of the power is also computed.

Within the single task execution, single knee lifts are automatically segmented to extract segment-level features. For each lift, the beginning of the movement (START), the moment of greater trunk-thigh proximity (PEAK) and the return to the ground (STOP) are identified. The stretch from START to PEAK identifies the lifting of the knee (leg angle decreases, up stage of the knee). The PEAK to STOP stretch identifies the descent stage (leg angle increases, down stage of the knee). The two stages are analysed separately so that performance differences in adduction and abduction could be assessed. The main purpose is again to describe the amplitude of the movement, i.e., the angle travelled, and its speed. Because of the fact that excursion is already well characterised by the previous analysis, speed is detailed. Therefore, angular speed on each stage (up/down) and on the overall lift (full START-STOP segment) are extracted in terms of maximum and mean values. In particular *mean_v*, differently from *v_ud*, represents the mean of the signed angular velocity in up (negative sign) and down (positive sign). This feature is considered to highlight the difference between the speed in up and in down: the sign of the parameter indicates which speed is greater; the magnitude how much they differ. The duration of the movement is also evaluated.

F. Statistical Analysis

The statistical analysis over the extracted features was conducted using the opensource tool Jamovi [29]. After applying Shapiro-Wilk test, a non-parametric analysis was considered as the parameters were not normally distributed; hence median, first and third percentile of the estimated features are reported in section III. In addition, violin plots representing estimation

	Features	Description (unit)
TASK	*exc_mean*	Mean leg angle excursion (deg)
	exc_std	Standard dev. leg angle excursion (deg)
	exc_max	Max leg angle excursion (deg)
	exc_min	Min leg angle excursion (deg)
	k_SV	KNEE joint Sway Volume (3D) (m^3)
	a_SV	ANKLE joint Sway Volume (3D) (m^3)
	k_SA_xy	KNEE Sway Area (Frontal) (m^2)
	a_SA_xy	ANKLE Sway Area (Frontal) (m^2)
	k_SA_yz	KNEE Sway Area (Transverse) (m^2)
	a_SA_yz	ANKLE Sway Area (Transverse) (m^2)
	f_max	Frequency at the maximum power (Hz)
	B90	Frequency at 90% of the power (Hz)
	v_ud	Mean magnitude of speed in up and down stages (deg/s)
	std_v_ud	Standard dev. of the magnitude of speed in up and down stages (deg/s)
SEGMENT	*max_v_up*	Max velocity[a] in up stage (deg/s)
	max_v_down	Max velocity[a] in down stage (deg/s)
	mean_v_up	Mean velocity[a] in up stage (deg/s)
	mean_v_down	Mean velocity[a] in down stage (deg/s)
	exc	Leg angle excursion in the segment(deg)
	max_v	Max velocity[a] in the segment (deg/s)
	mean_v	Mean velocity[a] in the segment (deg/s)
	dur	Duration of the segment (s)

[a] *Velocity with sign.*

TABLE I
KINEMATIC FEATURES DESCRIPTION

of statistical distribution of features for the PD group in the two types of execution, traditional (LA) versus gamified (BB) are also reported. The statistical comparison between LA and BB was performed using the non parametric Mann-Whitney U test, considering first executions at task-level then at up-down segments-level, for the PD group as a whole and for each subject independently. This kind of test is chosen because we assume executions of LA and BB, even by the same subject, to be independent and not perfectly paired, as each patient executed 2 full LA test (for each leg) versus 1 single BB test (for each leg). In addition, the test is not sensible to unbalanced sizes of the two groups compared (737 vs 112 in segments analysis, 60 vs 30 in full task comparison) [30]. Finally, radar plots of average values of kinematic features for each subject in the two tasks were considered: some significant examples are reported in the next section.

III. RESULTS

Table II contains the median, first and third percentile of all estimated parameters (task-level, segment-level) divided per type of execution (LA vs BB). From the table, it can be observed that parameters related to spatial properties of the movement under analysis (excursions, sway volumes and areas) are quite similar in both tasks, whereas velocity, frequency and duration parameters differ. In particular, the main frequency of the LA execution is almost double (duration in time twice lower, respectively) of the one in BB.

The following considerations may explain these numerical results: first, in the gamified setting, the subject follows a cadence that is defined by the parameter TURNONTIME set by the therapist, which includes also the time for the ball to

TABLE II
MEDIAN AND PERCENTILES OF EXTRACTED FEATURES

	Features (unit)	**Median (1^{st} percentile, 3^{rd} percentile)**	
		LA	***BB***
TASK	*exc_mean (deg)*	28.88 (24.42, 34.47)	28.21 (24.02, 33.97)
	exc_std (deg)	3.33 (2.50, 4.39)	3.41 (2.39, 4.14)
	exc_max (deg)	35.63 (30.79, 41.83)	32.43 (28.18, 38.47)
	exc_min (deg)	23.52 (13.15, 27.67)	23.01 (19.37, 30.62)
	k_SV (m^3)	0.12 (0.07, 0.19)	0.10 (0.06, 0.26)
	a_SV (m^3)	0.24 (0.13, 0.32)	0.22 (0.08, 0.48)
	k_SA_xy (m^2)	0.59 (0.50, 0.77)	0.66 (0.48, 0.91)
	a_SA_xy (m^2)	0.59 (0.43, 0.73)	0.48 (0.35, 0.79)
	k_SA_yz (m^2)	0.54 (0.40, 0.83)	0.53 (0.31, 0.89)
	a_SA_yz (m^2)	1.16 (0.83, 1.49)	1.30 (0.56, 1.97)
	f_max (Hz)	0.98 (0.70, 1.37)	0.44 (0.34, 0.44)
	B90 (Hz)	1.245 (0.88, 1.66)	0.83 (0.68, 1.03)
	v_up_down (deg/s)	62.44 (46.95, 94.10)	38.37 (33.38, 46.46)
	std_v_ud (deg/s)	15.20 (10.58, 20.35)	11.78 (9.04, 16.13)
SEGMENT	*max_v_up (m/s)*	-145.77 (-182.53, -116.60)	-126.87 (-156.62, -99.41)
	mean_v_up (deg/s)	-69.68 (-90.92, -48.73)	-44.19 (-56.34, -34.70)
	max_v_down (deg/s)	160.78 (118.65, 209.00)	104.62 (81.59, 129.85)
	mean_v_down (deg/s)	82.86 (54.29, 112.32)	31.17 (24.81, 41.93)
	exc (deg)	28.86 (22.97, 35.30)	29.60 (22.93, 35.073)
	max_v (deg/s)	174.30 (133.86, 219.59)	136.49 (103.91, 163.31)
	mean_v (deg/s)	-0.089 (-1.72, 1.52)	-0.24 (-1.19, 0.45)
	dur (s)	0.76 (0.56, 1.00)	1.58 (1.24, 1.85)

fall back in the initial position, ready to be hit. Secondly, the subject has a visual feedback of the leg height with respect to the ball height, set through BALLSTART, which could help the subject in reaching always the same height. Lastly, in LA task the subject is suggested to raise the leg as fast and as high as possible, but there is no guarantee that both aspects will be correctly achieved by the subject, who could favour, for instance, speed with respect to movement amplitude. These aspects are further investigated in the following subsections.

A. Task-level analysis

Fig. 4 shows violin plots for task-level kinematic features. Values are min-max normalised to allow simultaneous visualisation. As it can be appreciated, spatial parameters (excursions and sway areas and volumes) have similar median values for their distributions in LA and BB tasks, even though the

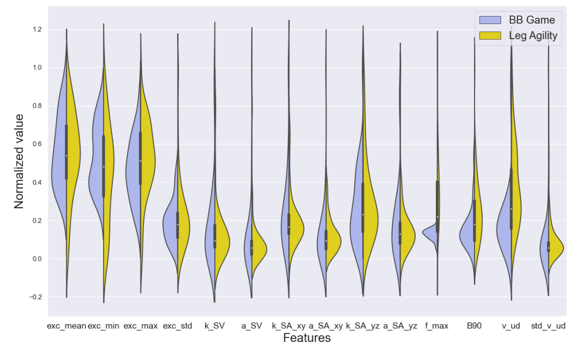

Fig. 4. Violin plots of task-level features normalised in LA and BB

violins are more or less spread depending on the parameter considered. Quite different behaviours are instead observed for frequency parameters and velocity. This result, however, is coherent with what already found in the inspection of median and percentiles: BB is fixing the cadence at which leg raises are performed, with evident effects also on the speed kept during the movement. Indeed, velocities are more widespread in LA, where the patient is left free to decide the pace (theoretically his maximum), resulting in an increased variability among subjects. Moreover, the discrete number of levels in the game seems to not allow to reach a data variability (characteristic of the subject) as wide as in LA. Lastly, the sizes of the two sets are unbalanced. The results of Mann-Whitney U test are reported in Table III. Significance threshold is set at $p < 0.05$. The results are aligned to what already hinted by violin plots: spatial measures (excursion, sway volumes and areas) are coherent between the two types of execution: the subjects tend to perform the same movement in terms of amplitude and lateral sway in the two tasks (with a proper setting of BALLSTART parameter in BB). Frequency of the movement and velocity are instead a discriminating parameter between the two tasks: the levels defined for TURNONTIME are not sufficient to elicit a movement cadence and velocity in BB comparable with the one in LA for all subjects.

An in depth analysis of this result for each subject was carried out plotting radar graph of features average values (again min-max normalised for visualisation) in all LA trials versus all BB trials performed by the same subject. Two relevant cases are shown in Fig. 5 (subject 5) and Fig. 6 (subject 15). As it can be appreciated, subject 5 has almost equivalent radar plots for both LA and BB, whereas subject 15 has a complete opposite behaviour, with almost no correspondence between features in the two tasks. Analysing the videos collected during the trials, it can be observed that for subject 5 the game was almost perfectly calibrated such that the executions of LA and BB were identically performed by the patient. Moreover, the subject did not seem influenced by the gamified setting of BB. Subject 15, instead, performed LA favouring higher speed and cadence but reduced amplitude; on the contrary,

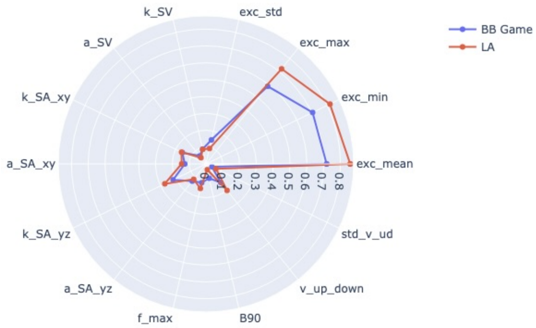

Fig. 5. Radar plots of task-level features in LA and BB (subject 5)

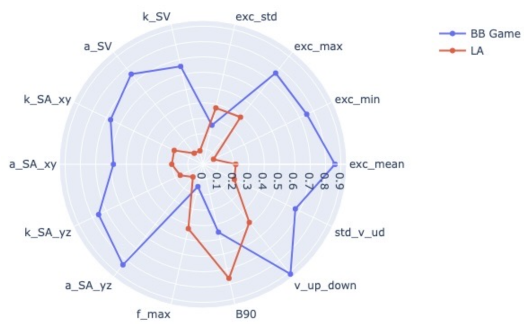

Fig. 6. Radar plots of task-level features in LA and BB (subject 15)

	Features	BB vs LA	p-value
S	max_v_down	32519	<.001
E	mean_v_down	21083	<.001
G	max_v_up	19288	<.001
M	mean_v_up	10427	<.001
E	exc	39389	0.436
N	max_v	26117	<.001
T	mean_v	36882	0.069
	dur	8709	<.001

TABLE IV
MANN-WHITNEY U TEST RESULTS AND SIGNIFICANCE

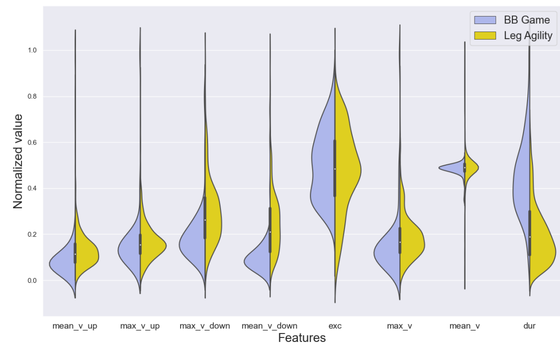

Fig. 7. Violin plots of segment-level features normalised in LA and BB

in the gamified setting of BB the subject performed much larger leg excursions, even larger than what was required to hit the ball. This result shows how this specific subject was affected by the goal-oriented nature of the task, that however allowed for a truer evaluation of the maximum excursion that the subject could reach with his legs. Similar behaviours are identified also in the other examined patients, with almost an even distribution (half and a half).

B. Segment-level analysis

Fig. 7 shows violin plots of the kinematic features for segment-level analysis. Again, values are min-max normalised to allow simultaneous visualisation. The results confirm the findings at task-level: excursions on single segments show similar distributions in the two tasks. About velocities, maximum and mean velocities in leg raise (up stage) and maximum velocity on segment have similar distributions with slightly shifted median values (higher for LA), as from Table II. More widespread are maximum and mean velocities in the down stage for LA with respect to BB: in the less restricted settings (LA), it is likely for the subjects to perform this stage in an uncontrolled manner, with an higher variability among subjects and trials. Distribution of feature $mean\_velocity$, instead, suggests that both in LA and in BB a similar symmetry in the speeds between up and down movement is maintained by subjects in the two tasks. Duration of segment is different between the two executions as expected, considering the already mentioned difference in movement velocities and cadence due to game settings.

	Features	BB vs LA	p-value
	exc_mean	766.0	0.868
	exc_min	640.0	0.173
	exc_max	621.0	0.123
	exc_std	760.0	0.824
	k_SV	758.0	0.809
T	a_SV	770.0	0.898
A	k_SA_xy	717.0	0.528
S	a_SA_xy	684.0	0.345
K	k_SA_yz	730.0	0.612
	a_SA_yz	777.0	0.951
	f_max	70.5	<.001
	B90	486.0	0.005
	v_ud	327.0	<.001
	std_v_ud	592.0	0.069

TABLE III
MANN-WHITNEY U TEST RESULTS AND SIGNIFICANCE

The results of Mann-Whitney U test are reported in Table III. Significance threshold is set at $p < 0.05$. The results are aligned to what already hinted by violin plots: excursion and mean velocity are coherent between the two types of execution. Indeed, the subjects tend to perform the same movement in terms of amplitude in the two tasks and with a similar symmetry in the up-down stages (e.g., if a subject moves leg faster in up stage and slower in down stage for LA, likely the same behaviour occurs in BB). Peaks and mean velocities in up and down stages are instead discriminant features between the two executions, as well as duration. An in-depth analysis was performed, considering LA and BB

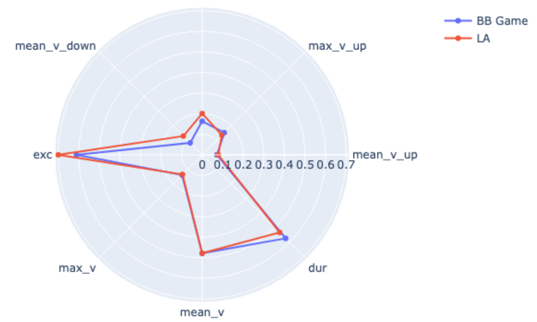

Fig. 8. Radar plot of segment-level features in LA and BB (subject 5)

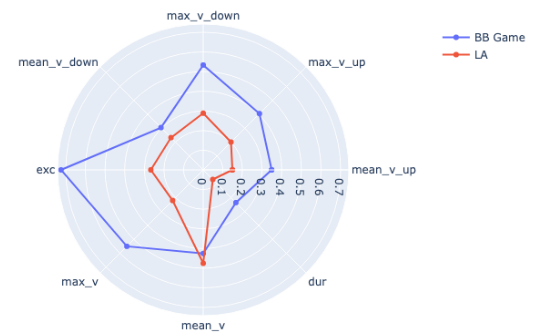

Fig. 9. Radar plot of segment-level features in LA and BB (subject 15)

segments grouped by subjects: Fig. 8 and Fig. 9 show radar plots of min-max normalised segment-level features for the same two previous significant cases, namely subject 5 and subject 15. As it can be observed, average values of segment-level features are almost perfectly overlapping for subject 5, denoting how the subject performed the two tasks in a very similar manner also considering this granularity. Subject 15, instead, shows a marked discrepancy between LA and BB. These behaviours are coherent with the comment reported in section III(A).

IV. Conclusions

Through the statistical analysis of objective and automatically-extracted kinematic features, this work proposes a comparison between traditional Leg Agility and a gamified version of the same motor task, the Bouncing Ball exergame, suitable for elderly affected by Parkinson's disease.

The experimental phase involved 15 parkinsonian subjects who performed both tasks in front of an acquisition and processing system based on Azure Kinect and its body tracking library. Virtual 3D skeletons reconstructing the subjects' motion during LA and BB trials were analysed by custom written MATLAB scripts to automatically estimate relevant kinematic features, either from the spatial, the temporal or the frequency domain. These features are organised in two levels, for analysis of the tasks at different granularity, i.e. task-level features and up-down segment-level features referring to a single cycle of leg movement. Both levels of analysis provide an insight on different aspects of the subjects' execution of LA and BB game.

From the statistical analysis of the extracted features in the two types of execution, traditional (LA) and gamified (BB), it was observed that either at segment-level or task-level, spatial features related to angular excursion, sway area, or volumes are similar. Hence, the subjects tend to perform the same leg raises in both tasks if the initial position of the ball in BB is properly calibrated to elicit the subject maximum movement excursion. With respect to velocity, duration, and frequency parameters, instead, it was observed that the gamified setting of BB inevitably influences the speed at which the subject performs the task. This results in a more controlled execution, partially losing the natural variability of LA which could contain relevant clinical information. Even though three levels of cadence/velocity (game parameter TURNONTIME) were employed, these levels are probably not tailored enough to the actual subjects to elicit a more natural execution at subjects' maximum speed in the task. For future experimental tests, additional levels should be employed. In addition, an automatic calibration procedure could allow to properly configure the game through a preliminary execution of traditional LA, so that the game is more adherent to the real motor skills of the examined subject.

The examples of subjects 5 and 15 reported in section III highlight how some PD patients are less behaviourally affected by the gamified setting of BB (subject 5), with respect to others (subject 15) who instead completely alter their performance when in a goal-oriented game. This aspect should be further investigated by enlarging the statistical sample size with additional subjects and/or additional BB trials. Furthermore, this aspect could be leveraged to solicit some specific aspects of the movement itself. For instance, in subjects who implicitly prefer the speed aspect during traditional LA, it may be appropriate to stimulate the amplitude aspect through the proper configuration of the game; whereas in subjects who prefer the amplitude aspect during traditional LA, it may be appropriate to stimulate the speed aspect during the game. This could lead to a more comprehensive assessment of both features with respect to traditional LA. Moreover, this could be achieved while simultaneously rehabilitating the subject on a specific kinematic feature and promoting greater motor and cognitive control using also specific cognitive stimulus from the game.

From these preliminary results, it is reasonable to conclude that BB exergame does not configure as a complete alternative to LA evaluation. Nevertheless, it could be employed as a complementary tool for a more thorough assessment and rehabilitation, through specific stimulation of motor aspects that a patient would not put in place autonomously.

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