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A new index to assess turning quality and postural stability in patients with Parkinson's disease

Luigi Borzì [a], Gabriella Olmo [a,*], Carlo Alberto Artusi [b], Margherita Fabbri [b], Mario Giorgio Rizzone [b], Alberto Romagnolo [b], Maurizio Zibetti [b], Leonardo Lopiano [b]

[a] Dept. of Control and Computing Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino, Italy
[b] Department of Neuroscience "Rita Levi Montalcini", University of Turin, Via Cherasco 15, Torino, Italy

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ABSTRACT

Parkinson's disease is a neuro-degenerative disorder characterized by the progressive death of dopamine neurons. This leads to delayed and uncoordinated movements, and impacts on the patients' motor performance with reduced movement intensity, increased axial rigidity and impaired cadence regulation. Turning provides privileged insights in postural instability and fall prediction, as it is regularly performed during daily activities, requires multi-limb coordination. The objective of this work was to define a Quality of Movement (QoM) index, inferred from inertial data related to turns, and strictly correlated with the patient's motor conditions, postural stability, and stage of the disease. Such a concise representation finds its main application in the remote monitoring of patients during daily activities at home. We have recorded and analyzed 180° turns in 72 patients, using inertial sensors embedded in the smartphone. We have set up an algorithm for binary classification of patients: *mild* vs. *moderate/severe* conditions, according to the Hoehn and Yahr scale of disease progression and disability degree. Our QoM index is defined as the *a posteriori probability* output by this binary classifier. It exhibits high correlation ($r = 0.73$) with the clinical score of postural stability, as well as with the average of four clinical scores related to movement impairment ($r = 0.75$). These results, together with the widespread smartphone use, provide a step in the direction of a practical, objective and reliable tool for PD patients remote monitoring in domestic environment.

1. Introduction and background

Parkinson's disease (PD) is the second most common neurodegenerative disorder after Alzheimer's [1]. Being age-related, its prevalence exceeds 1.9% over the age of 80. It involves both motor and non-motor symptoms, associated with the degeneration of dopamine neurons, mainly in (but not limited to) the *substantia nigra pars compacta* region of the brain stem. Due to its involvement in executive functions, motor control, motivation and gratification, a reduced dopamine level leads to delayed and uncoordinated movements, attention deficits, anxiety, depression, and psychiatric disorders, severely affecting quality of life [2].

Main PD motor signs and symptoms determine the so-called *Parkinsonian triad*, encompassing tremor, rigidity and bradykinesia (slowness of movement). Postural instability and akinesia (lack of movement) are other signs, often (but not always) related to advanced stages of the disease.

At present, no drug is recognized to stop the disease progression, and only symptomatic therapies are available [3]. Levodopa (L-dopa) is the gold standard drug for the control of PD motor symptoms [4]. However, after several years of treatment, it can bring about serious side effects such as involuntary movements (dyskinesia) as well as motor response fluctuations (wearing-off, ON-OFF periods). Actually, 70% of patients develop motor fluctuations after 9 years of L-dopa therapy [5]. The clinical approach to motor fluctuations implies careful adaptation of the drug posology to the response of each single patient. Such a personalized process is enabled by a timely monitoring of the patient's functioning during daily living [6].

The assessment of the course of PD is currently pursued in outpatient environment, usually by means of the UPDRS (Unified Parkinson's Disease Rating Scale) [7,8]. This evaluation encompasses six parts, including motor and non-motor symptom estimation. Part III, which is the most relevant for this work, is the clinical scoring of several motor skills: speech ability, facial expres-

* Corresponding author.
E-mail address: gabriella.olmo@polito.it (G. Olmo).

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siveness, tremor, rigidity, sensitivity of the fingers, hand mobility, leg agility, ability to get up from a chair, posture and postural stability, gait characteristics, bradykinesia and hypokinesia. The clinician assigns an integer score between 0 and 4 according to the severity of the considered sign. In addition, the Hoehn and Yahr (H&Y) scale is commonly used to evaluate the disease progression and disability degree. It ranges from 1 (minimal or no functional impairment) to 5 (wheelchair bound or bedridden unless aided) [9]. However, the recent Movement Disorder Society recommendations [10] suggest that the disease progression should be monitored at home during daily activities. In fact, motor fluctuations are very difficult to appreciate in a medical office, where the actual patient status may be affected by several confounding factors [11]. Hence, a remote monitoring implemented using low-cost instrumentation and self-managed by the patients themselves at home, could represent a very important tool for the clinicians [10].

The main goal of this work is to implement an objective *Quality of Movement (QoM)* index from inertial data related to turns, measured using wearable, cost-effective sensors. This index is designed so that it is strictly correlated with the patient's motor conditions, postural stability, and stage of the disease. This can enable remote control of patients while performing their daily activities at home, hence a timely assessment of motor fluctuations, risk of falls and progression of the disease.

Gait is heavily affected in PD patients, and many features of the gait cycle (i.e. single/double support, stance, swing duration; step and stride length and their variability) are related to disease progression [12–14]. Consequently, the gait of PD subjects has been addressed in many studies, even by means of wearable sensors. Inertial sensors have also been used to quantify the risk of falls among elderly people [15,14]. Experimental protocols usually encompass straight walking along a (typically) 10-m course in controlled environment [16,17]. However, the provided information may be difficult to generalize in free-living conditions. For example, in [18] a single sensor placed on the lower back of 30 PD subjects was employed to characterize ON vs. OFF state mobility. Subjects performed Time Up and Go (TUG) task, from which a specific feature, called Normalized Jerk Score, was extracted. Significance tests (i.e. *t*-test and Wilcoxon-test) were used to assess differences in patients during ON and OFF state. In [6] two inertial sensors were positioned on head and trunk of 15 PD patients and 15 elderly controls performing TUG; Wilcoxon tests between kinematic parameters (e.g. steps, angle, velocity) revealed the possibility of distinguishing healthy controls and PD patients, as well as variations in drug posology.

Among the several gait tasks performed during daily activities, many literature studies, as well as the clinical experience, recognize *turning* as a privileged activity to detect motor impairment in PD patients. Turning requires multi-limb coordination and continuous displacement of the center of mass. Spatially and temporally asymmetric stepping is required for each leg to travel a different distance while maintaining the same step time, and this provides information about dynamic balance aspects [19]. Not surprisingly, turning is strictly related to freezing of gait, postural instability, increased risk of falls and consequent injuries, mortality isolation, loss of confidence and depression [15,19–21]. On the other hand, the automatic assessment of turning is not trivial. Optical systems [21,22] ensure repeatability due to the controlled measurement environment, and lead to well-quantified and accurate results over short distances. Actually, these systems are widely accepted as *gold standards*. However, their high cost, long set-up time, expensive and cumbersome equipment, make their use unfeasible for frequent monitoring.

Despite the numerous studies on the gait characteristics of PD subjects using wearable sensors, only few of them focused on turn detection and analysis. Among them, we can mention [22], where the authors employed a single sensor placed on lower back, and carried on measures on a cohort of 20 PD and 13 elderly subjects with the objective of detecting turns both in ON and OFF states. The experimental protocol encompassed simulated daily activities, including free-walking, sit-to-stand, brushing teeth, ironing and turning. The achieved detection performance, measured in terms of sensitivity, specificity and accuracy, was 92%, 89% and 92% in ON, and 92%, 78% and 83% in OFF state. In [15], the authors carried on a study on 45 elderly and 10 young adults equipped with four inertial sensors, positioned on sternum, lower back and upper legs. Participants were asked to perform multiple 360° turns in both directions; the aim was to identify persons characterized by a high anamnestic risk of falls. Dynamic Time Warping of angular velocity signals of elderly participants and controls was implemented, and significant differences between the two classes were revealed. However, the method has not been applied to patients of neurodegenerative diseases. All the mentioned studies exhibit some limitations, namely: reduced PD patient cohort (maximum 30 PD patients); supervised experimental protocols; use of dedicated, generally multiple Inertial Measurement Units (IMUs). Moreover, no index of postural stability or objective measure with assessed correlation with clinical parameters was proposed.

Table 1
Samsung S5 mini sensors characteristics.

Sensor type	Range	Resolution	Sample frequency
Accelerometer	±2 g	40 mg	200 Hz
Gyroscope	± 2000 dps	60 mdps	200 Hz

In this paper, we address the inertial sensors embedded in smartphones as easy-to-use and widespread measurement tools. This approach fits the Digital Health Pathways [11], a pipeline defining guidelines for a patient-centered, large-scale platform exploiting wearable devices. We have collected data related to patient turns, and used them to define a Quality of Movement index. In order to validate the effectiveness of our index, it has been correlated with a number of UPDRS-part III items relevant for postural stability and progression of the disease.

The rest of this paper is organized as follows. In Section 2 we describe the experimental setup and the cohort of PD patients enrolled for this experiment, as well as the implementation of the QoM index. In Sect. 3 the achieved results are described and discussed, and in Section 4 conclusions are drawn.

2. Materials and methods

This study has been performed at the Regional Reference Center for Parkinson's disease and Movement Disorders, University Hospital *Città della Salute e della Scienza*, Turin, Italy. PD patients were asked to perform walking tests encompassing several 180° turns in both directions while wearing a smartphone, in order to measure inertial data and work out the QoM index.

2.1. Smartphone evaluation

A single Samsung S5 mini smartphone has been employed. The characteristics of the embedded inertial sensors have been evaluated in order to assess their suitability for the data acquisition process at hand (see Table 1). The sample frequency of 200 Hz is largely sufficient, given that human activity acceleration signals lie in the 0–20 Hz band [23]. The accelerometer dynamic range of ±2 g is adequate, given that typical signals range between ±1 g while walking and ±2 g during running [23,24], and that PD patients are likely not to reach these values. The ±2000 dps gyroscope dynamic range is similar to that of dedicated IMUs [25–27]. This confirms that the smartphone sensors are suitable for our application. We

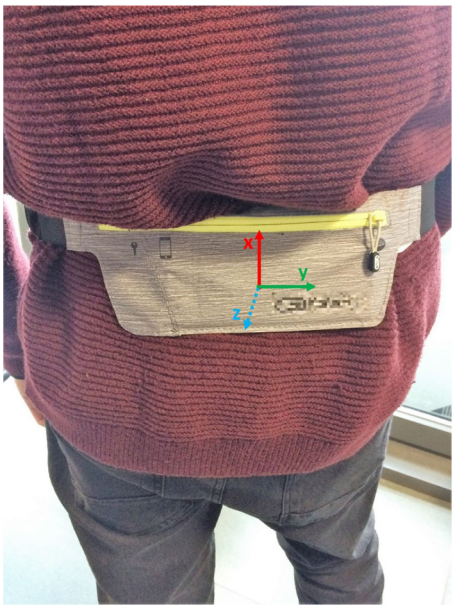

Fig. 1. Smartphone position adopted for the experiments.

have adopted proper measures to ensure that the sensor operations are not limited by either the Operating System or the application at hand. As for the identification of a suitable sensor location on the body, we have selected the lower back due to its comfort and closeness to the body center of mass, also in accordance with [28].

2.2. Data collection

A total number of 72 PD patients have been enrolled in the experiment. About 60% are males, and this reflects the prevalence of this pathology, that is unbalanced between the two genders. However, the demographic and clinical characteristics are not significantly different between the two groups; hence, for the sake of brevity, these are not separately reported in the rest of this paper. The inclusion criteria were: a clinical diagnosis of Parkinson's disease with motor symptoms, no major comorbidities or vision/cognitive impairments preventing them from accomplishing the required tasks. All PD participants were in *daily ON* state, meaning that they had taken their usual drug dose, and a variable time had elapsed since then.

Most patients (namely, 59 out of 72) have been enrolled during the pre-scheduled follow-up clinical visit. Hence, detailed clinical scores related to the entire UPDRS-part III were available, measured simultaneously to our experiments by clinicians with expertise in movement disorders.

Inertial data have been acquired during all the visiting time. Patients were equipped with the smartphone secured around the third lumbar vertebra with an elastic band, ensuring its adherence to the body (see Fig. 1). Then, they were asked by the clinicians to perform the several activities relevant for the UPDRS scoring, including free walking, turning with different angular amplitudes, standing-up, sitting-down, standing for several seconds and so on. These tasks, performed in semi-supervised conditions, are rather representative of activities carried out in domestic environment. However, during the visit the number of turns performed by each patient was rather limited (3.6 turns/patient on average, total of 213 turns recorded). On the other hand, for practical reasons (time, fatigue) it was not possible to ask these patients to perform further walking tasks after the visit.

Therefore, a second set of 13 PD patients were explicitly enrolled for our experiments, independently of their periodical follow-up neurological visit. These patients were asked to perform a Six-Minute Walking Test (6 MWT), selected for its easy setting up, patient tolerance and reproducibility [29], and, most important, its suitability for measuring multiple 180° turns in both directions. Subjects were equipped with the smartphone as previously described, and asked to walk back and forth along a 10-m hallway for 6 min at their preferred pace. They were free of using their usual walking aids, and of quitting the test in any moment and possibly resuming it. Given that these patients did not undergo a simultaneous complete neurological examination, the whole UPDRS-Part III was not evaluated. However, a recent H&Y score was available from anamnestic data, and confirmed by the clinicians supervising the experiments. The patients were binary classified into two groups: *mild (M)* vs. *moderate/severe (S)* motor and postural conditions. The first class corresponds to H&Y less than or equal to 2, whereas the second class encompasses patients with H&Y larger than 2. A total of 126 turns have been recorded, with an average of 9.7 turns/patient (59 turns in the *M* class, average 9.8 turns/patient, and 67 turns in the *S* class, average 9.6 turns/patient).

Table 2
Demographic and clinical characteristics of PD patients enrolled during pre-scheduled outpatients visit (G-PD1).

Number of patients	Mean age (years ± SD)	Disease duration	H&Y (mean ± SD)
59 (63% male)	69.2 ± 10.2	6.7 ± 5.3	2.14 ± 0.8

Table 3
Demographic and clinical characteristics of PD patients performing the 6 MWT (G-PD2).

Condition	Number of patients	Mean age (years ± SD)	Disease duration	H&Y
Mild (M)	6 (67% male)	68.2 ±3.9	6.2 ±1.7	≤2
Moderate/Severe (S)	7 (69% male)	75.2 ±5.3	15.2 ±4.5	>2

The main characteristics of the two patients subgroups (labelled G-PD1 and G-PD2 respectively) are summarized in Tables 2 and 3 . It is worth noticing that, as the objective of this paper is to devise an index capable of correlating with the motor status and the disease progression of PD patients, all the experiments have been carried out on patients characterized by different stages of the disease. The inclusion of a control group was not deemed pertinent, whereas the generalization to other conditions (e.g. frailty in the elderly population), although extremely interesting and challenging, is beyond the scope of the present paper.

The study has been conducted in accordance with the Declaration of Helsinki and approved by the local Ethics Committee. Participants received detailed information on the study purposes and execution, and written informed consent for observational study was obtained. Demographic and clinical data were noted anonymously. Tests were performed under the supervision of clinical personnel to ensure patients' safety.

All patients agreed to the video-taping of the procedure after receiving suitable explanations and being guaranteed that he/she cannot be identified and the videotapes are not made available to persons different of the authorized ones. However, in this preliminary study we have decided not to rely on such video recordings. In fact, given that our objective was to assess a QoM index using inertial data from turns, the only relevant information in this phase was the fact that the patient was performing a turn. The annotation of this specific piece of information was deemed not sufficient to justify the time possibly spent by a clinician to view the whole video sequence, given also the fact that a clinician was in any case present

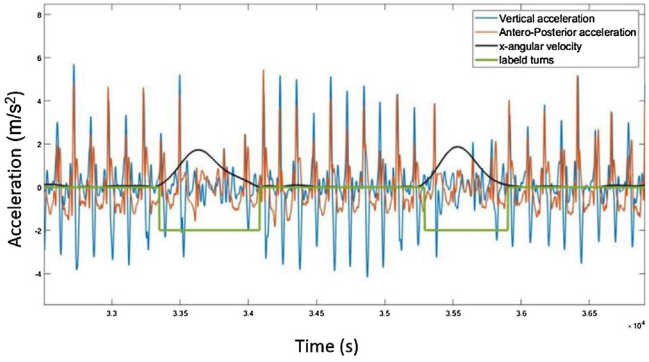

Fig. 2. Acceleration and angular velocity signals related to walking and turning activities. For better visualization, the *x*-component of angular velocity was low-pass filtered (fc = 0.5 Hz), removing high frequency noise. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

during the test. In any case, the video was recorded to enable possible future research. A chronometer was run simultaneously to the test session, and turns and gait abnormalities (e.g. freezing of gait episodes) were manually annotated by the clinical and technical personnel. Inertial data from the embedded sensors were collected and locally stored by means of SensorLog, a commercial app for Android 6.0. Once collected, data were exported in CSV format and processed offline using MATLAB version 2018a for Windows 10.

2.3. Signal labeling

Based on activity annotations while patients performed the experimental protocols, we were able to accurately define the starting and ending points of each turning event, using a MATLAB Graphical User Interface. For the sake of simplicity and in order to avoid confounding factors and increase the detection performance in view of an automated turn detection, only 180° turns were considered. It is worth noticing that 180° turns allow one to get a significant insight of the patient's clinical condition, as some gait features may not be reliable with smaller turn angles. Fig. 2 reports sample amplitudes of the acceleration signal. The correlation between its components decreases during turning, compared to the activity of straight walking. Moreover, the *x*-component amplitude of the angular velocity (black line) exhibits a neat increasing and subsequently decreasing pattern. The area under this curve yields information on the amplitude of the turn, whereas the green line denotes the identified signal segments related to turns.

2.4. The QoM index

First of all, some pre-processing was performed on the registered data. The signals were re-calibrated in order to compensate for deviations of sensors from the ideal positioning and to make gait signal patterns uniform. The method proposed in [30] was applied, consisting of 3-axis accelerometer orientation correction by applying a quaternion rotation transformation to the device raw data. After mean-removal, inertial data were de-trended and filtered with a second-order zero-lag Butterworth low-pass filter with cut-off frequency 20 Hz.

Then, inertial data segments related to turns were used to define the QoM index. This goal has been achieved as detailed in the rest of this section.

2.4.1. Preliminary evaluation

As a preliminary step in the direction of defining the QoM index, we wanted to answer the following question. Is it possible to devise a specific feature, measured from inertial data related to turns, which exhibits strong correlation with the UPDRS-Part III scores relevant for depicting the patient's motor conditions and postural stability? These latter have been identified as follows: Item 3.9 "arising from chair", 3.10 "gait", 3.12 "postural stability", 3.13 "posture", average among these, and H&Y stage.

In case such a feature was identified, it could be directly employed as a QoM index. In order to shed some light on this issue, we have performed a thorough literature analysis, and selected a large number of possible features, reported in Table. 4 . The selection has been based on the recognized capability to describe gait characteristics, postural control and motor impairment in healthy, frail, faller, and/or PD subjects, also affected by complications such as freezing of gait. A set of 77 features has been extracted from each of the 213 signal segments identified as 180° turns in the 59 G-PD1 patients; we have implemented the experiment on this subset because the whole UPDRS scores are available for this patients' group. All acceleration (α_x, α_y, α_z) and angular velocity (ω_x, ω_y, ω_z) components were kept separated. The Spectral Entropy is the Shannon entropy computed on the signal Fast Fourier Transform (FFT), whereas the Weighted Power Spectrum Peaks represents the product of amplitude and frequency values corresponding to the dominant harmonic in the FFT domain. The other features are self-explaining.

We have evaluated the Pearson correlation coefficient between each feature reported in Table 4 and the already mentioned UPDRS-part III scores assigned by neurologists during the outpatient visit, reported here for clarity: Item 3.9 "arising from chair", 3.10 "gait", 3.12 "postural stability", 3.13 "posture", average among them, H&Y stage.

Table 5 summarizes those features that exhibited at least moderate correlation ($r \geq 0.4$) with some of the addressed clinical indices. All associated *p*-values are in the range $[10^{-13}, 10^{-8}]$.

It can be noticed that only moderate correlation exists ($r \in [0.4, 0.5]$) between each of the selected features and the considered UPDRS-part III scores. This means that no feature of this set can

Table 4
List of all feature extracted for each turn.

Feature ID	Feature name	Source
1	Root Mean Square	[18,31,32]
2	Range	[33]
3	Standard Deviation	[18,31]
4	Jerk	[18]
5	Normalized jerk	[18]
6	Spectral Entropy	[34]
7	Spectrum Peaks	[35,34]
8	Normalyzed Spectrum Peaks	[34]
9	Weighted Power Spectrum Peaks	[35,34]
10	Harmonic Index	[36]
11	Low Power Frequency	[37]
12	Step variability	[38,39]
13	Stride variability	[35,37,38]
14	Symmetry	[37,38]
15	Step time	[38]
16	Stride time	[37,38]
17	Dominant frequency	[35,34,39]

Table 5
List of features showing at least moderate correlation with clinical motor scores. × denotes $r < 0.4$. P.S. = postural stability.

Feature	Component	H&Y	Gait	P.S.	Average
1	α_z	0.44	×	×	0.46
1	ω_y	×	×	0.4	0.4
2	α_z	0.46	×	×	0.49
4	α_z	0.46	×	0.44	0.5
7	α_z	×	×	×	0.41
17	$\alpha_\times$	×	0.4	×	×

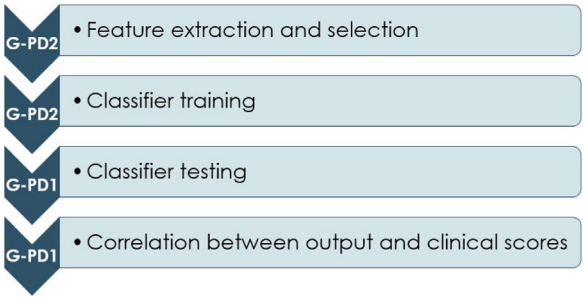

Fig. 3. Workflow of the procedure yielding the QoM index.

Table 6
List of features selected for binary classification.

Feature	Component	r	p-Value
1	$\omega_x, \alpha_z, \alpha_x$	0.66, 0.54, 0.49	<0.0001
2	ω_x	0.63	<0.0001
3	ω_x, α_z	0.63, 0.54	<0.0001
6	ω_x	0.55	<0.0001
9	ω_x, α_z	0.58	<0.0001

be directly employed as a QoM index with good reliability. From this preliminary analysis, it turns clear that it is necessary to use multiple features in order to achieve an improved correlation with the target. Consequently, we define a proper classification algorithm, fed with turn inertial data and exploiting multiple features as discussed in the following section.

2.4.2. QoM definition

Our method to achieve the QoM index is graphically depicted in Fig. 3. In order to exploit the mutual contribution of all features listed in Table 4, we tested several Machine Learning (ML) models input with the inertial data related to turns. We address a binary classification algorithm, capable of sorting patients into two classes: *mild (M)* and *moderate/severe (S)* motor conditions, defined as a H&Y stage ≤2 and >2 respectively. This choice is due to the fact that, even though the number of patients enrolled in this experiment is significant, nevertheless the number of turns performed is not sufficient to enable a finer multi-class sorting. It is worth noticing that the binary classification was available also for the 13 patients of the G-PD2 group, performing the 6 MWT; hence the related data, i.e. 126 turns (59 and 67 for *M* and *S* subjects respectively) was available for the algorithm training.

Even though the addresses classification is binary, nevertheless the classification algorithms actually output a continuous index, namely the *a posteriori probability* of belonging to either class. Hence, once a reliable binary classification is achieved, we propose to use this *a posteriori probability* as the definition of our QoM index.

2.4.2.1. Feature extraction and selection. The feature set reported in Table 4 was considered to train several ML models, using data of the PG-PD2 patients. In order to avoid overfitting, a feature selection was implemented as follows. Features exhibiting moderate/strong Pearson correlation coefficient ($r > 0.5$) with the target (i.e. *M* and *S* classes) were retained. Moreover, features exhibiting strong mutual correlation were discarded, in order to keep only relevant and non-redundant features. The final selected feature set is reported in Table 6.

Interestingly, 5 features over 9 are related to vertical angular velocity, which yields a measure of turning velocity and was previously stated to be sensitive to motor symptoms severity in [18,40].

2.4.2.2. Classification algorithm selection, training, validation and testing. As for the selection of a proper ML algorithm, Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA) were considered. For each model, the main parameters were exhaustively tuned, namely: kernel type, kernel scale and box constraint for SVM; number of neighbors, distance metric and distance weight for KNN; maximum number of splits, minimum leaf size and split criterion for DT; gamma and delta parameters for LDA. The classifiers were trained using G-PD2 patients, i.e. those who performed the 6 MWT and whose binary classification based on the H&Y scale was available. Given that the two input classes (*M* and *S*) were balanced, the cost parameter was not adjusted. The optimization was performed by minimizing the 10-fold cross validation error (i.e. maximizing the accuracy), and the performance was validated in terms of accuracy and Area Under the Curve (AUC). To this end, of the 126 available data segments related to turns, each algorithm was trained with 113 and validated with the remaining 13, and the procedure iteratively repeated. Moreover, in order to evaluate the generalization capability of each classifier, a Leave-One-Subject-Out (LOSO) validation was performed. It consists in training the classifiers with data from all subjects except one, which is then used for testing.

Table 7
10-fold cross validation results for different ML models and binary (*M* vs. *S*) classification.

Classifier	Parameters	Accuracy (%)	AUC
DT	Split criterion: cross entropy. Number of nodes: 17	85.7	0.88
KNN	Number of neighbors: 33. Distance metric: Euclidean. Distance weight: equal	88.1	0.93
Linear SVM	Kernel function: linear. Boxconstraint: 0.13	91.3	0.95
LDA	Delta: 1×10^{-6}. Gamma: 4×10^{-4}	92.1	0.97

Once the most performing ML algorithm was selected, we were able to work out the QoM index. We recall that this is defined as the *a posteriori* probability of belonging to either class, averaged on all turns performed by each patient involved in the experiment. At this point, the algorithm was tested on data belonging to G-PD1 patients, whose complete UPDRS-part III scores were available, in order to assess the correlation of the achieved QoM with the relevant motor scores. The Pearson correlation of the index with the main clinical scores was estimated, as discussed in the following section.

3. Results and discussion

The classification performance achieved by the ML algorithms addressed in Section 2 are reported in Table 7, implementing a 10-fold cross validation and in terms of accuracy and AUC. We recall that each algorithm has been implemented with exhaustively optimized parameters (see Section 2.4.2), tested and validated on 126 turns performed by 13 patients during the 6 MWT.

LDA turned out to provide the highest accuracy and AUC, with sensitivity, specificity and precision 95.5%, 88.1%, 90.1% respectively. In detail, this algorithm detects 95.5% of 180° turns that, with a probability of 90.1%, have been walked by patients belonging to the *S* class. For the sake of completeness, the confusion matrix provided by the LDA classifier is reported in Fig. 4. Of the 67 (59) turns performed by patients belonging to the *S* (*M*) classes respectively, 64 (52) were correctly classified only 3 (7) were misclassified.

LDA achieved the best results also in LOSO validation. In more detail, it correctly classified all 7 subjects belonging to the *S* class, and misclassified a single subject with *M* motor conditions. Hence,

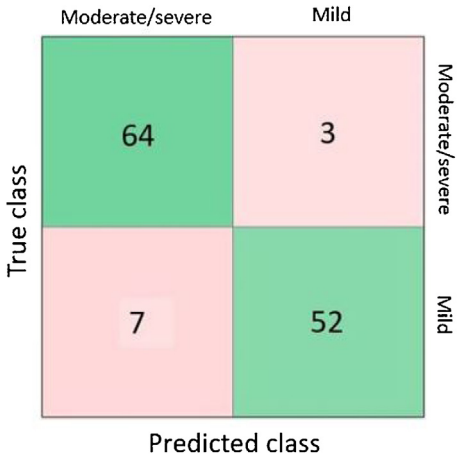

Fig. 4. Confusion matrix related to LDA classifier.

Table 8
Pearson correlation coefficient *r* between QoM index and some clinical UPDRS-part III scores.

Clinical score	*r*	*p*-Value
3.9 "arising from chair"	0.5	<0.0001
3.10 "gait"	0.61	<0.0001
3.12 "postural stability"	0.73	<0.0001
H&Y	0.66	<0.0001
Average Score	0.75	<0.0001

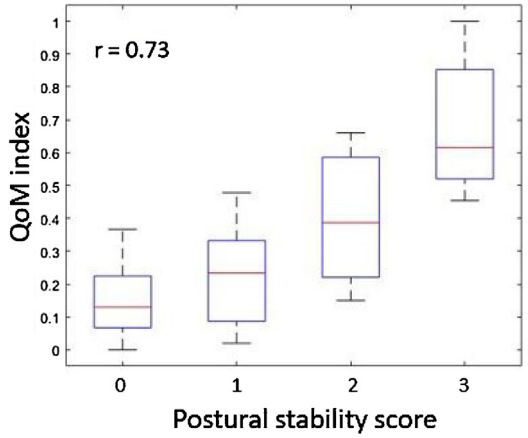

Fig. 5. Boxplot of QoM index vs. Item 3.12 "postural stability" score.

it achieved 100% sensitivity in detecting patients with severe motor conditions, and 88% precision. This witnesses a good generalization capability of the model. On the other hand, the number of misclassified subjects was 2 for SVM and KNN and 3 for DT.

Once trained on G-PD2 patients, the LDA classifier has been tested on the 59 PD subjects belonging to the G-PD1 sub-group, whose UPDRS scores were available. The correlation coefficients between the QoM index and the clinical scores are reported in Table 8. It can be appreciated that the QoM index exhibits strong correlation ($r > 0.7$) with the UPDRS Item 3.12 item "postural stability", and with the average UPDRS-part III motor score. The boxplot of QoM values as a function of the patients' "postural stability" score is also reported in Fig. 5.

We would like to stress that, in this evaluation, the QoM index evaluation involved 59 patients not engaged in the training phase, with different disease progressions and gait/postural impairment. Hence, we deem these results very meaningful, and significant to assess the reliability of the proposed method. Moreover, these patients performed a simple back-and-forth walking protocol (i.e. the task necessary for the clinical evaluation of UPDRS Item 3.10 "gait"), which is representative of walking during daily activities. Thus, we believe that the proposed method is suitable for an implementation in a domestic, unsupervised environment.

4. Conclusion and future developments

In this study, a Quality of Movement index, based on inertial data taken from 72 PD patients performing 180° turns and using a smartphone secured on the lower back, is proposed and validated. An optimized binary LDA classifier, capable of distinguishing *mild* vs. *moderate/severe* motor impairment based on the H&Y score, has been implemented. Its soft output, representing the *a posteriori* probability of belonging to either class, is proposed as the definition of the QoM index. This index exhibits strong correlation with UPDRS Item3.12 "Postural stability", and with the average of relevant UPDRS-part III motor scores. This demonstrates the effectiveness of the proposed QoM index to objectively assess the motor impairment level of PD patients. We would like to stress the relevance of strong correlation with the "postural stability" index, as this latter is directly related to the risk of falls, both in PD patients and in frail elderly subjects. Hence, it can be used to assess the risk of falls in these populations. In our view, this method represents a promising tool for achieving a global, concise picture of motor conditions, making use of cheap, widespread tools such as smartphones and implementing a simple task evaluation (only 180° turns were considered). Finally, a continuous monitoring may be devised, in order to measure motor fluctuations and regularly evaluate the treatment response.

A limitation of our method is that, at present, turn labeling is performed manually. In order to manage larger data sets, an automated turn detection is currently being implemented and validated using state-of-the-art gait analysis methods [21,22].

As future developments, new inertial data will be acquired from a wider patients cohort, and the QoM index will be correlated with fall risk scores obtained via Fall Risk Questionnaires. Finally, as freezing of gait and lower limb bradykinesia were assessed in a previous work [41], we also plan to integrate turn analysis in the same platform and to configure it as a stand-alone instrument, in order to build a sort of *electronic diary* of PD patients in domestic environments.

Declaration of Competing Interest

The authors report no declarations of interest.

References

[1] J. Jankovic, Parkinson's Disease: Clinical Features and Diagnosis, 2008.
[2] Z. Rihmer, X. Gonda, P. Dome, Depression in Parkinson's disease, Ideggyogyaszati Szemle 67 (7–8) (1994) 229–236.
[3] A.E. Lang, J.A. Obeso, Challenges in Parkinson's Disease: Restoration of the Nigrostriatal Dopamine System is Not Enough, 2004, May.
[4] C.C. Aquino, S.H. Fox, Clinical spectrum of levodopa induced complications, Mov. Disord. 30 (1) (2015) 80–89.
[5] C.W. Olanow, K. Kieburtz, O. Rascol, W. Poewe, A.H. Schapira, M.M. Emre, H. Nissinen, M. Leinonen, F. Stocchi, Factors predictive of the development of Levodopa-induced dyskinesia and wearing off in Parkinson's disease, Mov. Disord. 28 (8) (2013) 1064–1071.
[6] K. Lebel, C. Duval, H.P. Nguyen, R. Plamondon, P. Boissy, Cranio-caudal kinematic turn signature assessed with inertial systems as a marker of mobility deficits in Parkinson's disease, Front. Neurol. 9 (2018) 1–9.
[7] P. Martínez-Martín, A. Gil-Nagel, L.M. Gracia, J.B. Gómez, J. Martńez-Sarriés, F. Bermejo, Unified Parkinson's disease rating scale characteristics and structure, Mov. Disord. 9 (1) (1994) 76–83.
[8] C.G. Goetz, et al., Movement disorder society-sponsored revision of the unified Parkinson's disease rating scale (MDS-UPDRS): scale presentation and clinimetric testing results, Mov. Disord. 23 (15) (2008) 2129–2170.
[9] C.G. Goetz, W. Poewe, O. Rascol, C. Sampaio, G.T. Stebbins, C. Counsell, N. Giladi, R.G. Holloway, C.G. Moore, G.K. Wenning, M.D. Yahr, L. Seidl,

Movement disorder society task force report on the Hoehn and Yahr staging scale: status and recommendations, Mov. Disord. 19 (9) (2004) 1020–1028.
[10] A.J. Espay, J.M. Hausdorff, A. Sanchez-Ferro, J. Klucken, A. Merola, P. Bonato, S.S. Paul, F.B. Horak, J.A. Vizcarra, T.A. Mestre, R. Reilmann, A. Nieuwboer, R.E. Dorsey, L. Rochester, B.R. Bloem, W. Maetzler, A roadmap for implementation of patient-centered digital outcome measures in Parkinson's disease obtained using mobile health technologies, Mov. Disord. Clin. Pract. (2019) 1–7.
[11] J. Klucken, R. Kr, Management of Parkinson's disease 20 years from now: towards digital health pathways, J. Parkinson's Dis. 8 (2018) 85–94.
[12] S. Rezvanian, T. Lockhart, C. Frames, R. Soangra, A. Lieberman, Motor subtypes of Parkinson's disease can be identified by frequency component of postural stability, Sensors (Basel, Switzerland) 18 (4) (2018).
[13] J. Shah, L. Pillai, D.K. Williams, S.M. Doerhoff, L. Larson-Prior, E. Garcia-Rill, T. Virmani, Increased foot strike variability in Parkinson's disease patients with freezing of gait, Park. Relat. Disord. 53 (4) (2018) 58–63.
[14] L. Bizovska, Z. Svoboda, M. Janura, M.C. Bisi, N. Vuillerme, Local dynamic stability during gait for predicting falls in elderly people: a one-year prospective study, PLOS ONE 13 (5) (2018) 1–7.
[15] M. Ghahramani, F. Naghdy, D. Stirling, G. Naghdy, J. Potter, M. Roach, Assessing the risk of fall in older people through turning test, MeMeA 2018 – 2018 IEEE International Symposium on Medical Measurements and Applications, Proceedings (2018) 1–6.
[16] N. Haji Ghassemi, J. Hannink, C.F. Martindale, H. Gaßner, M. Müller, J. Klucken, B.M. Eskofier, Segmentation of gait sequences in sensor-based movement analysis: a comparison of methods in Parkinson's disease, Sensors 18 (1) (2018) 1–15.
[17] J.C.M. Schlachetzki, J. Barth, F. Marxreiter, J. Gossler, Z. Kohl, S. Reinfelder, H. Gassner, K. Aminian, J. Klucken, M. Eskofier, Wearable sensors objectively measure gait parameters in Parkinson's disease, PLOS ONE (2017) 1–18.
[18] M. Miller, S.J. Ozinga, A.B. Rosenfeldt, J.L. Alberts, Quantifying turning behavior and gait in Parkinson's disease using mobile technology, IBRO Rep. 5 (January) (2018) 10–16.
[19] S. Mellone, M. Mancini, L.A. King, F.B. Horak, L. Chiari, The quality of turning in Parkinson's disease: a compensatory strategy to prevent postural instability? J. NeuroEng. Rehabil. 13 (2016) 1–9.
[20] A. Sánchez-Ferro, M. Elshehabi, C. Godinho, D. Salkovic, M.A. Hobert, J. Domingos, J.M.T. van Uem, J.J. Ferreira, W. Maetzler, New methods for the assessment of Parkinson's disease (2005 to 2015): a systematic review, Mov. Disord. 31 (9) (2016) 1283–1292.
[21] M. Son, C. Youm, S. Cheon, J. Kim, M. Lee, Y. Kim, J. Kim, H. Sung, Evaluation of the turning characteristics according to the severity of Parkinson's disease during the timed up and go test, Aging Clin. Exp. Res. 29 (6) (2017) 1191–1199.
[22] M.H. Pham, M. Elshehabi, L. Haertner, S. Del Din, K. Srulijes, T. Heger, M. Synofzik, M.A. Hobert, G.S. Faber, C. Hansen, D. Salkovic, J.J. Ferreira, D. Berg, A. Sanchez-Ferro, J.H. van Dieën, C. Becker, L. Rochester, G. Schmidt, W. Maetzler, Validation of a step detection algorithm during straight walking and turning in patients with Parkinson's disease and older adults using an inertial measurement unit at the lower back, Front. Neurol. 8 (2017) 1–9.
[23] A. Godfrey, R. Conway, D. Meagher, G. ÓLaighin, Direct measurement of human movement by accelerometry, Med. Eng. Phys. 30 (December (10)) (2008) 1364–1386.
[24] V. Grigas, V. Eidukynas, A. Domeika, Acceleration based evaluation of the human walking and running parameters, J. Vibroeng. (3) (2009) 506–510.
[25] T. Iluz, E. Gazit, T. Herman, E. Sprecher, M. Brozgol, N. Giladi, A. Mirelman, J.M. Hausdorff, Automated detection of missteps during community ambulation in patients with Parkinson's disease: a new approach for quantifying fall risk in the community setting, J. NeuroEng. Rehabil. (2014) 1–9.
[26] A. Suppa, A. Kita, G. Leodori, A. Zampogna, E. Nicolini, P. Lorenzi, R. Rao, F. Irrera, L-DOPA and freezing of gait in Parkinson's disease: objective assessment through a wearable wireless system, Front. Neurol. 8 (2017).
[27] K. Bettecken, F. Bernhard, J. Sartor, M.A. Hobert, M. Hofmann, T. Gladow, J.M.T. Van Uem, I. Liepelt-Scarfone, W. Maetzler, No relevant association of kinematic gait parameters with health-related quality of life in Parkinson's disease, PLOS ONE 12 (5) (2017) 1–11.
[28] C. Pérez-López, A. Samà, D. Rodríguez-Martín, A. Català, J. Cabestany, E. De Mingo, A. Rodríguez-Molinero, Monitoring motor fluctuations in Parkinson's disease using a waist-worn inertial sensor, International Work-Conference on Artificial Neural Networks IWANN 2015: Advances in Computational Intelligence, vol. 9094 (2015) 461–474.
[29] N. Venkatesh, S. Thanikachalam, J. Satyanarayanamurty, A. Maiya, T. SenthilKumar, S. Sridevi, Six minute walk test: a literary review, Sri Ramachandra J. Med. 4 (2011) 30–34.
[30] M.D. Tundo, E. Lemaire, N. Baddour, Correcting Smartphone orientation for accelerometer-based analysis, MeMeA 2013 – IEEE International Symposium on Medical Measurements and Applications, Proceedings (2013) 58–62.
[31] M.D. Latt, H.B. Menz, V.S. Fung, S.R. Lord, Acceleration patterns of the head and pelvis during gait in older people with Parkinson's disease: a comparison of fallers and nonfallers, J. Gerontol. – Ser. A Biol. Sci. Med. Sci. 64 (6) (2009) 700–706.
[32] B. Huijben, The effect of walking speed on quality of gait in older adults, Gait Posture 65 (2019) 112–116.
[33] A. Galán-Mercant, A.I. Cuesta-Vargas, Differences in trunk accelerometry between frail and non-frail elderly persons in functional tasks, BMC Res. Notes 7 (1) (2014) 1–9.
[34] M. Ponti, P. Bet, C.L. Oliveira, P.C. Castro, Better than counting seconds: identifying fallers among healthy elderly using fusion of accelerometer features and dual-task timed up and go, PLOS ONE 12 (4) (2017) 1–21.
[35] A. Weiss, T. Herman, N. Giladi, J.M. Hausdorff, Objective assessment of fall risk in Parkinson's disease using a body-fixed sensor worn for 3 days, PLOS ONE 9 (5) (2014).
[36] C.J.C. Lamoth, P.J. Beek, O.G. Meijer, Pelvis-thorax coordination in the transverse plane during gait, Gait Posture 16 (2) (2002) 101–114.
[37] S.M. Rispens, M. Pijnappels, K. van Schooten, P.J. Beek, A. Daffertshofer, J.H. van Dieën, Consistency of gait characteristics as determined from acceleration data collected at different trunk locations, Gait Posture 40 (1) (2014) 187–192.
[38] R. Moe-Nilssen, J.L. Helbostad, Estimation of gait cycle characteristics by trunk accelerometry, J. Biomech. 37 (1) (2004) 121–126.
[39] A. Weiss, T. Herman, N. Giladi, J.M. Hausdorff, New evidence for gait abnormalities among Parkinson's disease patients who suffer from freezing of gait: insights using a body-fixed sensor worn for 3 days, J. Neural Transm. 122 (3) (2015) 403–410.
[40] A.L. King, M. Mancini, K. Priest, A. Salarian, F. Rodrigues-De-Paula, F. Horak, Do clinical scales of balance reflect turning abnormalities in people With Parkinson's disease? J. Neurol. Phys. Ther. 36 (March (1)) (2012) 25–31.
[41] L. Borzí, M. Varrecchia, G. Olmo, C.A. Artusi, M. Fabbri, M.G. Rizzone, A. Romagnolo, M. Zibetti, L. Lopiano, Home monitoring of motor fluctuations in Parkinson's disease patients, J. Reliab. Intell. Environ. 5 (2019) 145–162.