

Low-Complexity Inertial Sensor-based Characterization of the UPDRS Score in the Gait Task of Parkinsonians

Federico Parisi,
Gianluigi Ferrari
CNIT, Research Unit of Parma
and University of Parma, Italy
parisi.fed@gmail.com
gianluigi.ferrari@unipr.it

Matteo Giuberti
Xsens Technologies B.V.
The Netherlands
matteo.giuberti@xsens.com

Laura Contin
Telecom Italia, Italy
laura.contin@telecomitalia.it

Veronica Cimolin
Polytechnic of Milan, Italy
veronica.cimolin@
biomed.polimi.it

Corrado Azzaro,
Giovanni Albani
Istituto Auxologico Italiano
Piancavallo (VB), Italy
[c.azzaro,g.albani]
@auxologico.it

Alessandro Mauro
Istituto Auxologico Italiano
Piancavallo (VB), Italy
and University of Turin, Italy
mauro@auxologico.it

ABSTRACT

In this paper, we focus on the Gait Analysis (GA) for patients affected by Parkinson's Disease (PD) using a wireless Body Sensor Network (BSN) equipped with Inertial Measurement Units (IMUs). We estimate spatio-temporal parameters and other kinematic variables to characterize the gait, in both Parkinsonians and healthy people. Gait features are compared with scores assigned by neurologists within the Unified Parkinson's Disease Rating Scale (UPDRS), with the ultimate goal of automatically determining the UPDRS score of the Gait Task (GT) carried out by Parkinsonians. Preliminary results show a high correlation between a few gait parameters (such as double support, stride length, and thigh range of rotation) and UPDRS scores.

Keywords

Parkinson's Disease, Gait Analysis (GA), Inertial Measurement Unit (IMU), Unified Parkinson's Disease Rating Scale (UPDRS)

1. INTRODUCTION

Parkinson's disease (PD) is one of the most common neurodegenerative disorder, affecting 6.3 million people worldwide [1]. Main symptoms are related to difficulties in body movements, including bradykinesia, tremor at rest, postural instability, rigidity and gait impairments, beside a general progressive degeneration in the ability of performing motor tasks. Levodopa and dopamine antagonist are usually effective at managing the Parkinsonians' symptoms in the

early stage of the disease, but all the current dopamine-replacement therapies have shown a loss of efficacy over time and have been associated with long-term motor complications, such as dyskinesias and motor fluctuations [2]. The clinical evaluation of symptoms' severity is a fundamental task to define an effective therapy. In order to obtain a more objective and quantitative assessment of the motor tasks, semi-quantitative evaluation scales are often used, such as the Unified Parkinson's Disease Rating Scale (UPDRS) [3], which can help neurologists in determining the progress degree of the disease. This kind of assessment, however, may be difficult and impractical, as it requires a continuous monitoring of the patients by medical personal or self-reports by patients (which may likely be unreliable). In recent years, several works have appeared with the aim of helping clinicians with technologies that can provide an automatic assessment of Parkinsonians motor tasks. In this direction, studies have been conducted for the *sit-to-stand* task [4], the *leg agility* [5–7] task, *tremors* [8], and many others.

Gait is probably the motor task that mostly affects PD patients' daily life and independence, being very sensitive to fluctuations between the periods in which the drug's effect is active and those in which it is not (ON-OFF state fluctuations). More generally, gait is representative of the global ability of patients to perform complex motor tasks. For these reasons, many works have appeared in the literature with focus on Gait Analysis (GA) for Parkinsonians [9–11]. Classical GA systems are based on foot switches [12], Ground Reaction Forces (GRF) [10], and optoelectronic [13] systems. All these kinds of technologies are difficult to use in controlled clinical environments and often require external and expensive infrastructures. Inertial Measurement Unit (IMU)-based GA is currently the most adopted alternative approach, because it is cost-effective, reliable, and easy to use [14–16].

The goal of this work is to accurately estimate gait parameters using an IMU-based Body Sensor Network (BSN) and relate them to the UPDRS scores assigned by neurologists. The acquired information can be used to evaluate the severity of gait impairments and automatically assign UPDRS

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. To copy otherwise, to republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee.

BODYNETS 2014, September 29-October 01, London, Great Britain

Copyright © 2014 ICST 978-1-63190-047-1

DOI 10.4108/icst.bodynets.2014.257054

scores to the patients. Due to the preliminary nature of the work, we focus on the validation and the accuracy level of the estimated gait parameters and to a high-level evaluation of their relation with the UPDRS scores.

The structure of this paper is the following. In Section 2, we describe the Gait Task (GT) for UPDRS evaluation, the experimental set-up, and the signal processing approach used to estimate gait spatio-temporal parameters and other kinematic variables. Experimental results are presented and discussed in Section 3. Conclusions are finally drawn in Section 4.

2. METHODS

2.1 Description of the Gait Task

In the GT, the patient is asked to walk spontaneously away from the examiner for at least 10 m and in straight line, then to turn around and return to the starting point. This exercise should be performed in an obstacle-free environment and the initial/final acceleration phases should be discarded to avoid border effects in the analysis. The parameters of interest are the ones strictly related to the gait characteristics, such as: the stride amplitude and speed; the cadence; the gait cycle time; parameters related to the turning phase; the variability between left and right steps; and the movement of the upper limbs.

2.1.1 UPDRS Evaluation

The Movement Disorder Society (MDS)-UPDRS is the most popular rating system used by clinicians for assessing the severity and the variety of parkinsonian symptoms and its high reliability has been proved in different studies [17]. The evaluation of gait is included in the motor examination part (Part III) [18] and consists in assigning a score to patients from 0 to 4. In particular, a UPDRS score equal to 0 corresponds to normal walking; UPDRS scores 1 and 2 are assigned to patients who are able to walk independently but present some minor (UPDRS score 1) or substantial (UPDRS score 2) impairments, such as slow walking, short steps, and festination; finally, if the patient is not able to walk without any help, it is necessary to evaluate the level of assistance needed to perform the walking task or if he/she is not able to walk at all (UPDRS score from 3 to 4).

2.2 Experimental Set-up

2.2.1 Subjects

A group of 24 PD's patients is used in the experiments considered in this work. The group includes 17 males and 7 females with average age equal to 65.9 years (max = 79 years, min = 31 years) and standard deviation equal to 12.3 years. Furthermore, 4 healthy subjects (average age = 65.5 years, std = 2.88 years), labeled with a UPDRS score equal to 0, are also included in the dataset as a benchmark and to increase the rating range. Comparison between inertial and optical data is performed on a heterogeneous subgroup of 5 persons (3 males and 2 females), including both healthy subjects (3) and Parkinsonians (2).

2.2.2 Hardware description

Our goal is to exploit the sensor configuration used in previous works [5] in order to maximize the number of motor



Figure 1: Considered experimental testbed.

tasks that can be evaluated without changing the sensors' placement — a change may be uncomfortable for the patient. In particular, we used a BSN formed by Shimmer (Sensing Health with Intelligence, Modularity, Mobility, and Experimental Reusability) nodes [19]. A Shimmer node is a small and low-power wireless sensing platform that can capture and communicate a wide range of sensed data in real time. The main module is a compact wearable device (size: 53 mm x 32 mm x 25 mm; weight: 22 g) provided with: a TI MSP430 microcontroller; Bluetooth (Roving Networks RN-42) and IEEE 802.15.4-compliant (TI CC2420) radios; an integrated 2 GB microSD card slot; a 450 mAh rechargeable Li-ion battery; and a triaxial accelerometer (Freescale MMA7361). Moreover, the device is designed so that different external sensing modules can be easily connected. The 9DoF Kinematic Sensor expansion module, which is supplied with a triaxial gyroscope (InvenSense 500 series) and a triaxial magnetometer (Honeywell HMC5843), has been used. The sampling rate is set at 102.4 Hz. For validation purposes, additional data were recorded for a limited group of subjects, using a Vicon optoelectronic system able to provide the 3D coordinates of passive markers positioned on specific anatomical landmarks of the subject with an accuracy of approximately 0.21 mm.

2.2.3 Experimental Testbed and Acquisition

Each patient is equipped with 3 Shimmer nodes (one per thigh, one on the chest) attached to the body with Velcro straps. The sensors are placed trying to align the x axis to the upward-downward direction, the y axis to the right-left direction, and the z axis with the antero-posterior direction. The BSN configuration is shown in Figure 1. All the considered subjects are asked to walk, at their preferred speeds, in an obstacle-free environment for a variable distance between 7 m and 15 m and then to turn around and go back to the starting point¹. A total of 38 complete trials were recorded, as some patients performed the task in both ON and OFF conditions. All the trials have been evaluated by the same neurologist, in order to increase the homogeneity of the assessment. A non-integer scale with intermediate scores ($\cdot 5$) has been used to label the trials in which the neurologist was undecided between consecutive (integer) UPDRS scores. In

¹The acquisitions have been taken in different locations and, due to the lack of space, it has not always been possible to perform the task walking continuously for at least 10 m, as the MDS suggests. However, our results show that the travelled distance is sufficient to correctly extract the desired parameters.

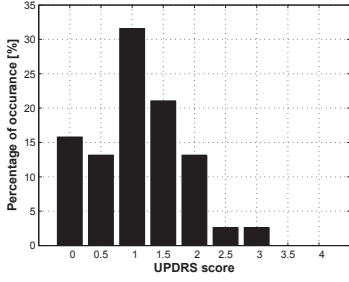


Figure 2: Distribution of the 38 UPDRS scores assigned for the GT trials.

Figure 2, the distribution of the 38 UPDRS scores for the GT is shown. The testbed for data validation is the same described in our previous work. The interested reader is referred to [5,6] for more details.

2.3 Gait Characterization

2.3.1 Estimation of Temporal Parameters

Even though human gait is a complex movement that involves many muscles and joints, it normally has a relevant rhythmic and repetitive component. The first step to analyze gait is “to break” its repetitive complex body movements into simpler blocks, denoted as *gait cycles*. In order to identify a complete gait cycle, it is necessary to detect two fundamental events for each leg: the Heel strike (*HS*) (i.e., instant at which the foot touches the ground) and the Toe-off (*TO*) (i.e., instant at which the foot leaves the ground). In particular, a gait cycle starts with the *HS* of a foot and ends with the following *HS* of the same foot. Therefore, five fundamental events can be identified:² right *HS* (HS_R), left *TO* (TO_L), left *HS* (HS_L), right *TO* (TO_R), right *HS* (HS_R).

In order to detect the five fundamental events characterizing a gait cycle, we propose an innovative approach based on proper processing of the accelerometric signal of the chest-mounted sensor device. The x , y , and z components represent, respectively, the vertical, the medio-lateral, and the antero-posterior accelerations. Typical acceleration patterns of a healthy subject and of a Parkinsonian, measured by the chest accelerometer during walking, are shown in Figure 3. By following a heuristic approach, a preliminary visual investigation was performed manually extracting the *HS* and *TO* events and labeling them from the optical ground truth data synchronized with the accelerometer signal. From the results in Figure 3, it can be observed that *HS*s are located in proximity of peaks of the vertical and antero-posterior accelerations. Physically, this is due to the fact that, just before the *HS* instant, the trunk reaches the maximum vertical acceleration (because the body is falling toward the ground) and also the maximum frontal acceleration (because the body is moving forward and then suddenly stops after the foot contact). Even though the peaks in both vertical and antero-posterior accelerations are very close, experimental results show that the vertical peak is more accurate to detect the exact *HS* instants. In the same way, it can be noticed that

²If not specified, we always refer to a right gait cycle.

the contralateral *TO* is located in correspondence to a local minimum of the antero-posterior acceleration, after the *HS* peak. In order to automatically distinguish between right and left events, the medio-lateral acceleration component is considered. In Figure 3, a few illustrative trunk acceleration signals (relative to consecutive gait cycles) are shown. It can be concluded that, although the accelerations in the healthy subject are more defined and have wider excursions, the described features can be easily identified also in the accelerometric data recorded for the Parkinsonian.

We now describe in detail the algorithm used for the estimation of the *HS* and *TO* events. The *first step* consists in low-pass filtering the recorded accelerometer signals with a fourth-order zero-lag Butterworth filter with bandwidth equal to 20 Hz: this is expedient to reduce high frequency noise components. In order to avoid attenuation effects in vertical acceleration, caused by an imperfect alignment of the sensors with the direction of the gravity, the 3D orientation of a Shimmer node, in the Earth frame, is estimated through an orientation filter based on a gradient descent algorithm [20]. The contribution of the gravity force is then subtracted from the correctly aligned acceleration component and the linear vertical acceleration can be obtained. The resulting signal is then processed to detect all the positive peaks, denoted as P_{HS} , discarding the ones with a magnitude lower than 25% of the maximum peak value.

In the *next step*, local minima in the antero-posterior acceleration inside the interval $[P_{HS}, P_{HS} + 0.4 \text{ ms}]$ are searched. The nearest one, after P_{HS} , is selected as *TO*. In order to correctly label the features for each leg, we consider the slope m of the line passing through the value of the medio-lateral acceleration sample corresponding to the instant of the first detected *HS* (HS_1) and the value of the sample coinciding with the following *TO* instant (TO_1). If $m > 0$, then a left gait cycle is starting, so that HS_1 is labeled as HS_L and TO_1 as TO_R ; if $m < 0$, HS_1 is labeled as HS_R while TO_1 as TO_L . The following *HS* and *TO* are labeled consequently, alternating right and left labels.

Once the *HS*s and *TO*s for each leg have been identified, the following temporal parameters can be calculated for the k -th gait cycle.

- Gait Cycle Time (*GCT*) (dimension: [s]): the time interval between the *HS* of a foot to the next *HS* of the same foot. In particular:

$$GCT_{R/L}(k) = HS_{R/L}(k+1) - HS_{R/L}(k)$$

- Stance Time (*ST*) (adimensional, percentage): the time percentage (relative to the corresponding gait cycle) during which a foot is in contact with the ground. In particular:

$$ST_{R/L}(k) = 100 \times \frac{TO_{R/L}(k) - HS_{R/L}(k)}{GCT_{R/L}(k)}$$

- Swing Time (*SW*) (adimensional, percentage): the time percentage (relative to the considered gait cycle) during which a foot is not in contact with the ground. In particular:

$$SW_{R/L}(k) = 100 - ST_{R/L}(k)$$

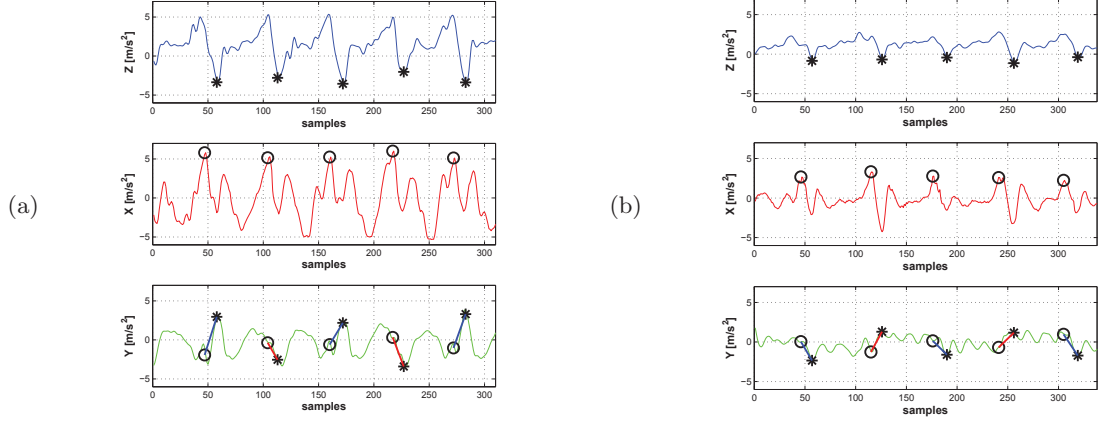


Figure 3: Recorded trunk accelerations for (a) healthy subject and (b) Parkinsonian with mild symptoms (UPDRS score equal to 1.5). Circles and asterisks denote, respectively, HS and TO events. In the medio-lateral acceleration, HS points are connected with following TO points by a line whose slope allows to discriminate left leg (blue line, positive slope) from right leg features (red line, negative slope).

- Double Support (DS) (adimensional, percentage): the time percentage (relative to the considered gait cycle) during which both feet are in contact with ground. This happens twice during a gait cycle: at the beginning and at the end of one foot's stance phase. The first DS phase is denoted as Initial Double Support (IDS) and the second one is denoted as Terminal Double Support (TDS). They can be expressed as follows:

$$IDS(k) = 100 \times \frac{TO_L(k) - HS_R(k)}{GCT(k)}$$

$$TDS(k) = 100 \times \frac{TO_R(k) - HS_L(k)}{GCT(k)}$$

Finally, the DS can be given the following expression:

$$DS(k) = IDS(k) + TDS(k).$$

A quantity related to DS , denoted as Limp, is defined as follows:

$$Limp(k) = |IDS(k) - TDS(k)|.$$

2.3.2 Estimation of Spatial Parameters

Gait spatial parameters are those related to distance and speed. The most frequently considered parameters are the following.

- Stride Length (SL) (dimension: [m]): the distance travelled from the HS of one foot to the following HS of the same foot.
- Stride Velocity (SV) (dimension: [m/s]): the average linear velocity of a foot during the gait cycle.
- Step Length ($StepL_{R/L}$) (dimension: [m]): the distance travelled from the HS of one foot to the HS of the other foot.
- Step Velocity ($StepV_{R/L}$) (dimension: [m/s]): the average linear velocity of a foot during a step.

As for the temporal parameters, step length and velocity are estimated using a single accelerometer placed on the trunk. In particular, considering that human gait can be simply described by an inverted pendulum model, the vertical displacement h (dimension: [m]) of the Center of Mass (CoM) can be used to estimate the forward distance S (dimension: [m]) traversed at each step. During walking, the CoM usually lies within the pelvis but its movements have been often approximated using a sensor device placed in proximity of the second sacral vertebrae [15]. In the same way, in our case, we assume that the vertical displacement of the sensor attached to the chest and the one of the CoM are similar. As described in [15], the relationship between vertical and forward displacements is given by the following equation:

$$S = K2\sqrt{lh - h^2} \quad (1)$$

where l is the length of the leg (dimension: [m]) and K is an empirically calibrated constant. The vertical displacement h can be obtained by double integration of the linear vertical acceleration a_v (dimension: [m/s²]). More precisely, for the i -th sample, the vertical velocity v_v (dimension: [m/s]) of the trunk can be computed as

$$v_v(i) = v_v(i-1) + a_v(i)\Delta$$

where $v_v(0)$ is assumed to be equal to 0 and Δ represents the sampling period (dimension: [s]). Then, the position p_v (dimension: [m]) of the trunk at the i -th sample can be expressed as

$$p_v(i) = p_v(i-1) + v_v(i)\Delta$$

where $p_v(0)$ is set to 0. The position data $p_v(i)$ are finally high-pass filtered (fourth-order zero-lag Butterworth filter with cut-off frequency set to 0.1 Hz) to remove integration drift and the total displacement amplitude is then calculated as the difference between the maximum and the minimum values of the trunk position during each step cycle (i.e., the time interval between the HS of one foot and the HS of the other foot). Considering the k -th gait cycle, the vertical

displacement of the trunk for the right step (h_R , dimension: [m]) can be obtained with the following expressions.

$$h_R(k) = \max_{i=HS_R(k)}^{HS_L(k)} p_v(i) - \min_{i=HS_R(k)}^{HS_L(k)} p_v(i)$$

where $HS_R(k)$ ($HS_L(k)$) indicates the first sample of the k -th HS for the right (left) leg. The value of the vertical displacement during a left step (h_L) can be calculated in the same way. The step lengths ($StepL_{R/L}$) are estimated using (1) and step velocities ($StepV_{R/L}$) are obtained from the step lengths and the duration of the step cycles. Stride spatial parameters can be finally obtained by adding the parameters associated with the right and left steps for each gait cycle.

2.3.3 Estimation of Additional Kinematic Variables

Important information about the ability of the patients to perform the GT are provided by joint angles and segment inclinations of the lower limbs [21]. The used sensor configuration allows us to retrieve only the data regarding the thighs' segments. In particular, angular rate signal measured by the gyroscopes on both thighs is integrated during each gait cycle in order to find the instantaneous inclination angle of the thighs. For the i -th sample of the angular velocity signal, the value of the instantaneous angle $\theta(i)$ (dimension: [deg]) can be calculated from the thigh angular velocity $\omega(i)$ (dimension: [deg/s]) and the sampling period Δ using the following equation:

$$\theta(i) = \theta(i-1) + \omega(i)\Delta.$$

The initial angle $\theta(0)$, at the beginning of each cycle, is set to zero. The Range of Rotation (RoR) (dimension: [deg]) of the right thigh (the RoR of the left thigh can be calculated in the same way), inside the k -th gait cycle, is assumed to be equal to the difference between the maximum and minimum values of the instantaneous angle, i.e.:

$$Thigh\ RoR_R(k) = \max_{i=HS_R(k)}^{HS_R(k+1)} \theta(i) - \min_{i=HS_R(k)}^{HS_R(k+1)} \theta(i).$$

During the experiments, we also collect the maximum values of the angular velocity in each gait cycle for both thighs.

3. RESULTS AND DISCUSSION

3.1 System Validation

The error in estimating of the spatio-temporal gait parameters, defined as the difference between the values obtained with the reference optoelectronic system and the ones found with the proposed BSN-based system, is shown in Table 1. The accuracy of the system in estimating the thighs' inclination has already been validated in [5]. The average estimation errors for the considered parameters, shown in Table 1, are comparable to those obtained in other studies, with both similar and different methods [14,15,22], and are sufficiently low to be considered almost negligible for our goals. In particular, the HS and TO estimation errors are likely to be systematic error (they have always the same sign) and could thus be corrected at a later stage.

3.2 Evaluation of UPDRS Scores

Using the presented methods, we analyzed more than 20 gait parameters. However, here we only present the obtained

Table 1: Estimation error of the gait parameters compared to the ones obtained from the optoelectronic reference system

Parameter	Mean	STD
HS	24.5 ms	6.6 ms
TO	18.3 ms	13.1 ms
GCT_R	0 ms	17.7 ms
GCT_L	6.85 ms	19.65 ms
ST_R	16.2 ms	32.55 ms
ST_L	15.45 ms	26.65 ms
DS	51 ms	59 ms
SL	4.23 cm	4.94 cm

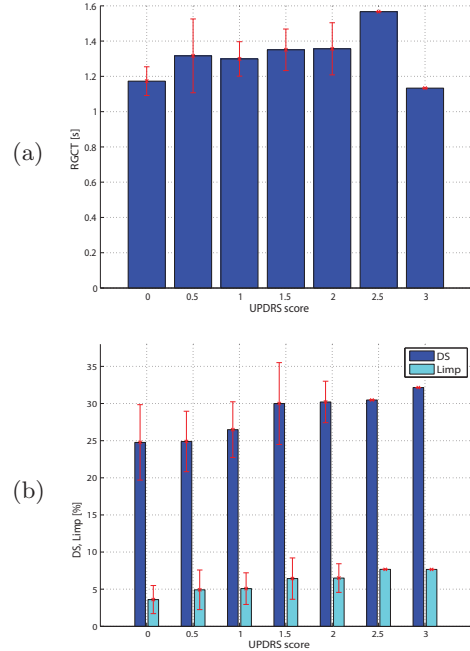


Figure 4: Mean values (colored bars) and standard deviations (confidence intervals) of relevant temporal parameters ordered by UPDRS class: (a) GCT_R ; (b) DS and $Limp$.

results relative to the parameters which turned out to be more significant for automatic UPDRS scoring.

For what concerns the temporal parameters, as observed in other works [9], the main indicators of gait impairments are the GCT , the DS , and the $Limp$. In Figure 4, their average values, together with the corresponding confidence intervals, are shown. It can be observed that these variables tend to grow for increasing values of the UPDRS score. In particular, the trend of GCT is more irregular because patients, who are not able to walk normally, often tend to make shorter steps while maintaining a high cadence. The increasing trend is more evident for DS and $Limp$, which are almost linearly increasing functions of the UPDRS score. Stance and Swing parameters are not considered because their variation between UPDRS scores did not appear to be relevant.

In Figure 5 (a), SL average values and standard deviations

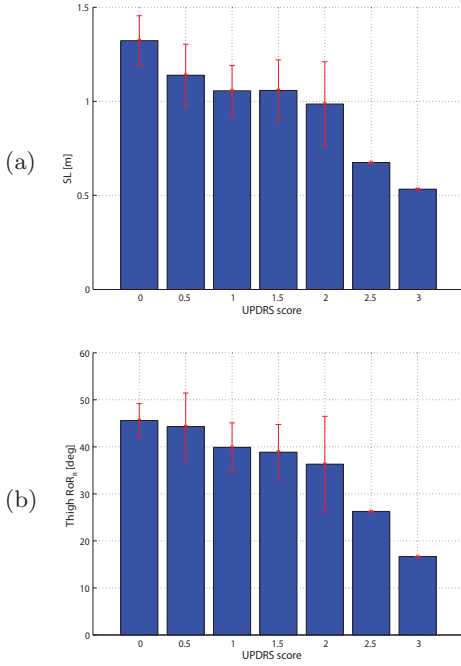


Figure 5: Mean values (colored bars) and standard deviations (confidence intervals) of (a) SL and (b) $Thigh\ RoR_R$ as functions of the UPDRS score.

are shown. A decreasing trend, for increasing values of the UPDRS score, is evident. The velocity follows the same trend, but results are not shown for lack of space. It can be observed a decrement of approximately 60% between the SL value associated with UPDRS score equal to 0 and the SL value associated to a UPDRS score equal to 2.5 or 3. As for the spatial parameters, the RoR of one thigh (the other one has the same behavior) decreases almost linearly from UPDRS score 0 to UPDRS score 3, with a relative reduction of approximately 60%, as shown in Figure 5 (b). The angular velocity peak has a similar trend and the relative reduction (between UPDRS values 0 and 3) is on the order of 40% — results are not shown here for lack of space.

Finally, we graphically visualize the relationship between the considered relevant parameters and the UPDRS score assigned by neurologists. In Figure 6, average $SL - Thigh\ RoR_R$ pairs for all the trials (each pair is associated with a single trial of a patient) are shown on the same plane. Each point is colored in accordance to the UPDRS score assigned to the patient. For each UPDRS cluster, the centroid is denoted by a different-colored star. Furthermore, all centroids are connected by a piece-wise linear line in order to show the parameters' trend for increasing UPDRS scores. A (red) straight line represents a smoothed version of the global trajectory. It can be clearly observed that the centroids move toward the bottom-left corner for increasing values of the UPDRS score. This result is consistent with the clinical observation of typical Parkinsonian walking, in which patients with more severe gait impairments show shorter stride lengths and, in general, a more limited movement range in the lower limbs. Another pair of parameters, which is representative of the UPDRS score, is given by $Limp$ and SL . The corresponding

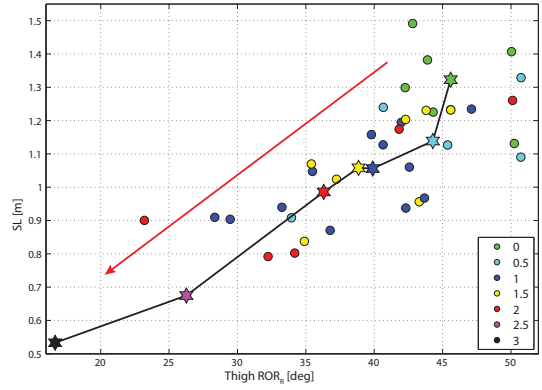


Figure 6: Average $SL - Thigh\ RoR_R$ pairs for all trials (circles), colored in accordance to the UPDRS score. The centroids of all clusters of pairs associated to the same UPDRS score are shown as stars. The red line shows a smoothed version of the global data trend.

results are shown in Figure 7. In this case, it can be observed that the centroids tend to move, for increasing values in UPDRS, to the right-bottom corner, i.e., to the region characterized by higher $Limp$ and lower SL . We remark that a few pairs are far from the main trajectory because neurologists might take into account, for the assignment of a UPDRS score, other qualitative variables, such as the movement of the upper limbs, that cannot be assessed with the used sensor configuration.

We underline that the monotonic trends observed in Figure 6 and Figure 7 are coherent with similar trends observed, considering different kinematic features, for the Leg Agility task of Parkinsonians [6]. This suggests that the proposed approach might be “universal,” i.e., that all the UPDRS tasks could be eventually analyzed by finding characteristic “trajectories” of proper kinematic features directly related to UPDRS assigned by neurologists.

4. CONCLUSIONS

In this paper, we characterized the GT of Parkinsonians through the estimation, using an inertial-based BSN, of typical spatio-temporal parameters and other kinematic variables. A novel low-complexity approach, based on the use of three inertial sensors, was used to find relevant gait features representative of the UPDRS score assigned by neurologists. The obtained experimental results show that spatial parameters and the level of mobility of the thighs have a clear decreasing trend for increasing UPDRS scores. On the other hand, temporal features, such as DS and $Limp$, tend to increase linearly with the UPDRS score. Taking into account the preliminary nature of this work, the presented results can be considered promising and motivate further investigations to design a system for automatic detection of the UPDRS score of the GT in PD's patients.

5. ACKNOWLEDGMENTS

This work is partially supported by the Italian Ministry of Health (RF-2009-1472190).

6. REFERENCES

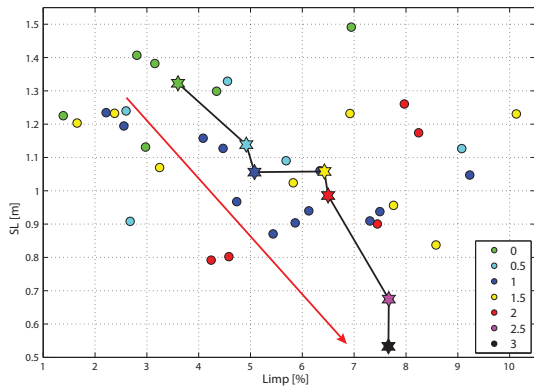


Figure 7: Average *Limp* - *SL* pairs for all trials (circles), colored in accordance to the UPDRS score. The centroids of all clusters of pairs associated to the same UPDRS score are shown as stars. The red line shows a smoothed version of the global data trend.

- [1] European Parkinson's Disease Association.
- [2] B. Chen, S. Patel, T. Buckley, et al. A web-based system for home monitoring of patients with Parkinsons Disease using wearable sensors. *IEEE Transactions on Biomedical Engineering*, 58(3):831–836, March 2011.
- [3] S. Fahn and R. L. Elton. *Recent Developments in Parkinson's Disease*, volume 2, chapter Unified Parkinson's Disease Rating Scale, pages 153–163. Macmillan Health Care Information, Florham Park, NJ, USA, 1987.
- [4] D. Giansanti, G. Maccioni, F. Benvenuti, and V. Macellari. Inertial measurement units furnish accurate trunk trajectory reconstruction of the sit-to-stand manoeuvre in healthy subjects. *Medical and Biological Eng. and Comput.*, 45(10):969–976, October 2007.
- [5] M. Giuberti, G Ferrari, L. Contin, et al. On the characterization of leg agility in patients with Parkinson's Disease. In *Proc. of 10th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, pages 1–6, Cambridge, MA, USA, May 2013.
- [6] M. Giuberti, G Ferrari, L. Contin, et al. Linking updrs scores and kinematic variables in the leg agility task of parkinsonians. In *Proc. of 11th International Conference on Wearable and Implantable Body Sensor Networks (BSN)*, Zurich, Switzerland, June 2014.
- [7] D. A. Heldman, D. E. Filipkowski, D. E. Riley, et al. Automated motion sensor quantification of gait and lower extremity bradykinesia. In *Proc. of the 34th Annual Int. Conf. of the IEEE Eng. in Medicine and Biology Society (EMBS)*, pages 1956–1959, San Diego, CA, USA, August 2012.
- [8] A. Salarian, H. Russmann, C. Wider, et al. Quantification of tremor and bradykinesia in Parkinsons Disease using a novel ambulatory monitoring system. *IEEE Trans. on Biomedical Eng.*, 54(2):313–322, February 2007.
- [9] A. Salarian, H. Russmann, F. J. G. Vingerhoets, et al. Gait assessment in Parkinson's Disease: Toward an ambulatory system for long-term monitoring. *IEEE Trans. on Biomedical Eng.*, 51(8):1434–1443, August 2004.
- [10] S. Chien, S. Lin, C., et al. The efficacy of quantitative gait analysis by the gaitrite system in evaluation of parkinsonian bradykinesia. *Parkinsonism and related disorders*, 12:438–42, 2006.
- [11] S. T. Moore, H. G. MacDougall, J. Gracies, H. S. Cohen, and W. G. Ondo. Long-term monitoring of gait in Parkinson's disease. *Gait & Posture*, 26(2):200–207, July 2007.
- [12] W. Zijlstra, A. W. Rutgers, and T. W. Van Weerden. Voluntary and involuntary adaptation of gait in Parkinson's disease. *Gait & Posture*, 7:53–63, Jan 1998.
- [13] A. Ferrari, M. G. Benedetti, E. Pavan, et al. Quantitative comparison of five current protocols in gait analysis. *Gait & Posture*, 28:207–216, 2008.
- [14] K. Aminian, B. Najafi, C. Büla, P. F. Leyvraz, and P. Robert. Spatio-temporal parameters of gait measured by an ambulatory system using miniature gyroscopes. *Journal of Biomechanics*, 35(5):689–699, May 2002.
- [15] W. Zijlstra and A. L. Hof. Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. *Gait & Posture*, 18(2):1–10, October 2003.
- [16] A. Köse, A. Cereatti, and U. Della Croce. Bilateral step length estimation using a single inertial measurement unit attached to the pelvis. *Journal of neuroengineering and rehabilitation*, 9:1–9, Jan 2012.
- [17] A. Siderowf, M. McDermott, K. Kiebertz, et al. Test-retest reliability of the Unified Parkinson's Disease Rating Scale in patients with early Parkinson's disease: Results from a multicenter clinical trial. *Movement Disorder*, 17:758–763, 2002.
- [18] C. G. Goetz, S. Fahn, P. Martinez-Martin, et al. Movement disorder society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Process, format, and clinimetric testing plan. *Movement Disorders*, 22(1):41–47, January 2007.
- [19] A. Burns, B. R. Greene, M. J. McGrath, et al. SHIMMER - a wireless sensor platform for noninvasive biomedical research. *IEEE Sensors Journal*, 10(9):1527–1534, September 2010.
- [20] S. O. H. Madgwick, A. J. L. Harrison, and R. Vaidyanathan. Estimation of IMU and MARG orientation using a gradient descent algorithm. In *2011 IEEE International Conference on Rehabilitation Robotics (ICORR)*, pages 1–7, Zurich, Switzerland, June 2011.
- [21] A. Delval, J. Salleron, J. Bourriez, et al. Kinematic angular parameters in PD: Reliability of joint angle curves and comparison with healthy subjects. *Gait & Posture*, 28(3):495–501, October 2008.
- [22] A. M. Sabatini, C. Martelloni, S. Scapellato, and F. Cavallo. Assessment of walking features from foot inertial sensing. *IEEE Trans. on Biomedical Eng.*, 52(3):486–494, Mar 2005.