Med Biol Eng Comput
https://doi.org/10.1007/s11517-017-1728-5

ORIGINAL ARTICLE

Time measurement characterization of stand-to-sit and sit-to-stand transitions by using a smartphone

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Received: 2 June 2016 / Accepted: 4 October 2017

Abstract The aim of this study is to analyze a common method to measure the acceleration of a daily activity pattern by using a smartphone. In this sense, a numerical approach is proposed to transform the relative acceleration signal, recorded by a triaxial accelerometer, into an acceleration referred to an inertial reference. The integration of this acceleration allows to determine the velocity and position with respect to an inertial reference. Two different kinematic parameters are suggested to characterize the profile of the velocity during the sit-to-stand and stand-to-sit transitions for Parkinson and control subjects. The results show that a dimensionless kinematic parameter, which is linked to the time of sit-to-stand and stand-to-sit transitions, has the potential to differentiate between Parkinson and control subjects.

Keywords Parkinson · Accelerometer · Dimensionless kinematic parameter · Signal analysis · Sit-to-stand · Stand-to-sit

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1 Introduction

Getting up from a sitting position (Si-St) or sitting down from a standing position (St-Si) is one of the most practiced daily activities [1]. In order to guarantee the proper performance during the sit-to-stand-to-sit (Si-St-Si) transition, an optimal coordination, an adequate control of balance, mobility, muscular strength, and power output are required [2]. In particular, the population with Parkinson disease (PD) [3], and elderly adults [4] show a notable difficulty to perform these kinds of kinematic transitions. Hence, to study the Si-St and St-Si transitions, a thorough analysis in terms of kinematic methodology is necessary , in order to define a specific experimental protocol, a type of sensor, and a sensor of position. Later, the signal analysis will identify specific kinematic parameters which allow to classify movement patterns and, ultimately, to differentiate patients with PD from control subjects.

The physicians often use surveys to evaluate a kinematic movement. The surveys are based on the time measurements of daily activities [5]. For the case of patients with PD, the Hoehn and Yahr scale or the Unified Parkinson's Disease Rating Scale is commonly used to classify the severity of the patient [6]. In general, these measurements give a qualitative evaluation that cannot detect subtle kinematic differences. However, more sophisticated technologies, such as measurement force platforms [7] or optical movement detection systems [3], make it possible to record continuously the kinematic movements and, thereby, fulfill the information of pattern movements. Although the clinical application is not widely implemented due to the complexity of these technologies. These novel technologies also require expensive and medium-large equipment to measure and analyze the kinematic data. On the contrary, the Micro-electronic mechanical systems (MEMS) development brings devices that allow to measure the motion by using the small motion sensor devices (MSD). These components are promising alternatives for evaluating and recording kinematic movements in clinical or at-home environments [8]. Recent studies show the application of MSD in kinematic motion analysis and diagnosis of patients with PD [9] and gait analysis [10]. The MSD are capable of recording most of the kinematic movements, but later, a signal analysis of these movements is carried out to reveal significant kinematic parameters. These parameters will characterize the kinematic patterns that, ultimately, allow to differentiate between groups [11]. For example, Mellado et al. [12] proved that a MSD in a smartphone was used as a low-cost integration device to evaluate the balance and the mobility of the patient. Joundi et al. [13] demonstrated that a common accelerometer of a smartphone can measure a kinematic tremor frequency. This tremor frequency has shown to be equivalent to the tremor frequency measured by electromyography. Furthermore, Wile et al. [14] utilized a smartwatch to differentiate the temblor of patients with PD from patients with essential tremor (ET). To achieve that, they calculated the signal power of the first four harmonics.

The period of time to perform the Si-St and St-Si transitions is called transition duration (TD). This period of time is considered a relevant clinical index [15], which is obtained straightforward from the acceleration signal recorded by the accelerometer. Later, the identification of peaks and/or signal thresholds in the acceleration signal will allow to determine the TD [11, 16]. Additionally, a gyroscope is also widely used to register the angular position, which is also a valuable information for clinical purposes. For example, Weiss et al. [17] stated that the antero-posterior acceleration was used to estimate the TD in patients with PD and control subjects during the Si-St-Si test. To do that, a pattern was identified as M shape to characterize the acceleration versus time signal. Finally, the TD is delimited as the time interval between the highest peaks of the kinematic signal. However, this kinematic parameter cannot stand alone to distinguish between healthy and PD groups [11]. Nikfekr et al. [3] arranged a motion system of six cameras to capture the kinematic positions of seven retroreflective markers that were placed at the C7, T3, T6, T9, T12, L3, and sacrum of the patient's trunk. After that, the kinematic movements of the patient's trunk was recorded during a Si-St transition. The results showed that the patients with PD presented a greater flexion and angular velocity of the trunk in the sagittal plane (sp). These greater values explain why the TD decreases during the Si-St transition. Costa et al. [9] investigated the acceleration of the finger tapping and unbounded forearm movements between two points. The aim was to study the interpeak interval variability and beat decay (BD) of the auto-mutual information (AMI) value. Patients with PD and ET denoted greater values of BD-AMI than the control subjects. In addition, Farkas at al. [18] presented the acceleration signal to describe the tremor asymmetry between patients with PD and ET. A bilateral evaluation showed that some kinematic parameters, linked to the tremor frequency, allow to discriminate between PD and ET groups of patients. Salarian et al. [24] combined portable inertial sensors and an automatic analyzer to record and define several kinematic parameters of the Stand-Up and Go test. This method showed significant differences in the cadence when comparing patients with PD and control subjects. Despite that, the classic chronometer evaluation shows no significant difference. Adame et al. [19] developed a novel method called dynamic time warping to detect and evaluate the TD status of PD patients by using a gyroscope. Nevertheless, the TD measurements did not present statistical differences between the PD and control groups. Recently, Barrantes et al. [20] found several kinematic features in the accelerometry analysis of hand tremor (postural and rest positions) that distinguished first between healthy subjects and patients and, ultimately, between PD and ET patients with a 84.38% of discrimination accuracy.

The motion data recorded by a MSD and the post-processing analysis to evaluate the kinematic parameters allow to comprehend the transition. The measurement of the TD is often the most common kinematic parameter used in the research studies with a MSD [5]. The specific features of this device allow to accurately measure the TD [12, 16]. In some cases, the TD parameter is the only measurement carried out in some studies [17, 21], but usually, this parameter is combined with other kinematic parameters to dispose a more robust motion analysis. Following the latter approach based on several kinematic parameters in the time domain, it will be possible to differentiate patients with movements disorders [22].

The TD parameter evaluation did not bring successful results as a clinical index, mainly due to the variability of this kinematic parameter. As this parameter will not detect subtle behaviors between PD and control subjects when performing Si-St or St-Si transitions, therefore, the present study proposes to use dimensionless kinematic parameters; in this sense, the parameters will not depend on how fast or slow the movement transitions are performed.

These kinematic parameters are defined when the velocity profile is characterized during the Si-St and St-Si transitions. Finally, a statistical analysis is performed to identify which parameter has more chances to let us successfully differentiate between PD patients and control subjects.

2 Materials and method

2.1 Subjects

The trunk movements were measured in a group of 10 patients with PD and five control subjects. The patients with PD have an average age of 60 years old, with a range of 53 to 66 years old and seven out of 10 were women. All the patients with PD were under medical prescription. Nine out of the 10 patients present a scale III in the Hoehn and Yahr scale, which means intermediate-advanced level of PD. A total Unified Parkinson's Disease Rating Scale was of 40.1 ± 15.8, and UPDRS-motor scores of 19.1 ± 8.3 (4–31). The control subjects have an average age of 54 years old, with a range of 50 to 59 years old and three out of five were women. All control subjects were asked for their consent and were given detailed information about the study. The study was approved by the medical ethics committee of the Medical Faculty of the Universidad de Santiago de Chile (USACH).

2.2 Equipment

The acceleration measurements were recorded by using a smartphone. This device uses the MEMS technology and incorporates a triaxial piezoresistive accelerometer (LIS302DL model). This accelerometer disposes a dynamic scale between the range of ± 2 or ± 8 gravitational acceleration, which was previously selected by the user. The Seismograph application was used to record the experimental acceleration of the device in the three axes with a nominal frequency acquisition of 40 Hz.

2.3 Movement protocol

The acceleration measurement was performed by the smartphone that was placed on the lumbar vertebrae L2–L3 by using a belt. The axes of the accelerometer were defined as follows: x axis was perpendicular to the sp, z axis was perpendicular to frontal plane (fp), and y axis was perpendicular to the other two directions. In this sense, the path followed by the device corresponds to the path followed by the center of mass of the subject. The timed test of Si-St and St-Si transitions was categorized in four phases. Phase 1: the initial position of the person is sitting on a backless chair, of straight and with arms crossed on the chest. Then, the acceleration signal begins to be recorded. Phase 2: after recording a couple of seconds, the stand-up order is given and the subject begins the Si-St transition. Phase 3: once the subject finalizes the Si-St transition, it is recorded about 10 to 15 s. Phase 4: the sit down order is given and the subject begins St-Si transition. Once the subject finalizes the St-Si transition, another 10 to 15 s was recorded. This protocol was repeated five times in order to have five Si-St and five St-Si transitions.

2.4 Estimation of the absolute velocity and acceleration

Unlike the kinematic position information captured with optical movement detection systems [3], an accelerometer will record the motion information associated with a local reference. This local reference is defined by the three accelerometer axes. Initially, the velocity cannot be calculated by integrating the acceleration signal, because the signal is refereed to a mobile reference. Despite that the information of accelerometry and kinematic position are comparable in terms of quality, it is necessary to have into account the relative orientation of the accelerometer with respect to the gravitational vector [23]. Therefore, to estimate the acceleration with respect to a fixed reference, an algorithm is required to transform the coordinates. In general, these kinds of algorithms estimate the gravity components into the accelerometer axes [24].

Figure 1 shows the experimental configuration of a subject that carries the smartphone in his/her trunk to record the movement. The sequence of the images show how to perform a St-Si transition with the combination a-b-c or the Si-St transition with the combination c-b-a. The device is placed on the patient's trunk and the accelerometer axes are oriented as shown in Fig. 1. The x and z axes are disposed in the sp all the time. The acceleration signal is decomposed into the accelerometer axes when the device is recording. As the z axis of the accelerometer do not coincide with the horizontal direction, the accelerometer registered two terms: the acceleration of gravity (g) and the dynamic acceleration caused by the subject movement in the z direction. A similar situation occurs with the other two axes.

Generally, if the acceleration components are referred to, an inertial reference is more convenient, because these components can be linked to the v and h direction of a sp. Figure 2 shows the vectors used to determine the acceleration components in a fixed reference v and h. The vector a_x belongs to the acceleration component of the x axis. This vector is tilted an α angle with respect to the vertical direction in the sp.

Knowing the α angle and the two-dimensional rotation matrix (1), the acceleration components of the fixed

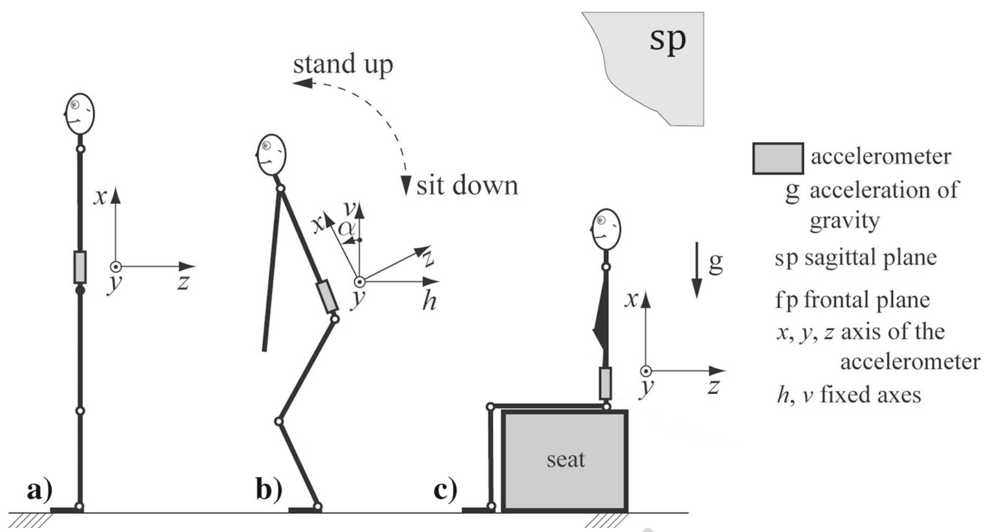

Fig. 1 The position of smartphone during the St-Si or Si-St transitions

reference $h - v$ can be obtained from the acceleration measurements referred to the mobile reference $z - x$.

$$\begin{Bmatrix} a_h \\ a_v \end{Bmatrix}_{h,v} = [S_\alpha] \begin{Bmatrix} a_z \\ a_x \end{Bmatrix}_{z,x} \rightarrow [S_\alpha] = \begin{bmatrix} cos(\alpha) & -sin(\alpha) \\ sin(\alpha) & cos(\alpha) \end{bmatrix} \tag{1}$$

It is assumed that the acceleration components recorded in the mobile axes a_x and a_z have a constant component, which is defined by the gravitational components a_{xg} and a_{zg}, respectively.

$$a_{xg} = g \cdot cos(\alpha) \tag{2}$$

$$a_{zg} = g \cdot sin(\alpha) \tag{3}$$

Replacing Eqs. 2 and 3 in Eq. 1, the rotation matrix which defined the acceleration in the fixed reference $h - v$ is achieved.

$$\begin{Bmatrix} a_h \\ a_v \end{Bmatrix}_{h,v} = \frac{1}{g} \begin{bmatrix} a_{xg} & -a_{zg} \\ a_{zg} & a_{xg} \end{bmatrix} \begin{Bmatrix} a_z \\ a_x \end{Bmatrix}_{z,x} \tag{4}$$

A singular case happens when the α angle is equal to zero, because the rotational matrix is simplified to the identity matrix. Therefore, the acceleration component at the x axis is constant and equal to g, while the acceleration component at the z axis is zero. To use Eq. 4, the transformation matrix components have to be known as a function of an instantaneous position. To do that, these components can be estimated by using a second degree polynomial in different signal segments or by using an averaging zero-phase FIR filter [25]. In this study, a low-pass filter, in particular a moving average filter with a Gaussian kernel, is applied to determine the transformation matrix components. The optimum value of the kernel's width is found when the error function is minimized. This function was applied to scan all the possible kernel's widths in a range of 0.5 to 10 s.

$$r(l) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(\sqrt{a_{xgi}^2(l) + a_{ygi}^2(l) + a_{zgi}^2(l)} - g \right)^2} \tag{5}$$

where a_{xg}, a_{yg}, and a_{zg} are the constants of acceleration components registered in the axes x, y, and z, respectively, l is the length of the moving average filter with a Gaussian kernel, and N is the number of points to define the aforementioned components. If the output value of the

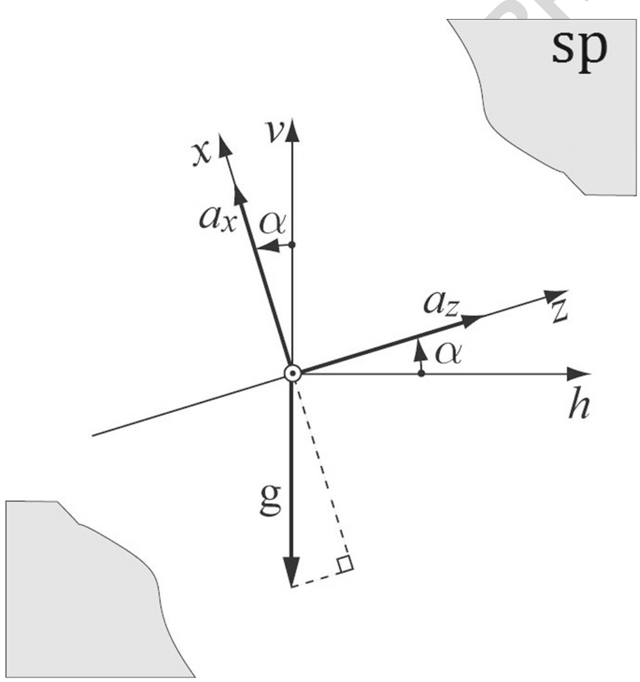

Fig. 2 Acceleration components a_x and a_z of the mobile reference $z - x$ with respect to the fixed reference $h - v$ in *sp*

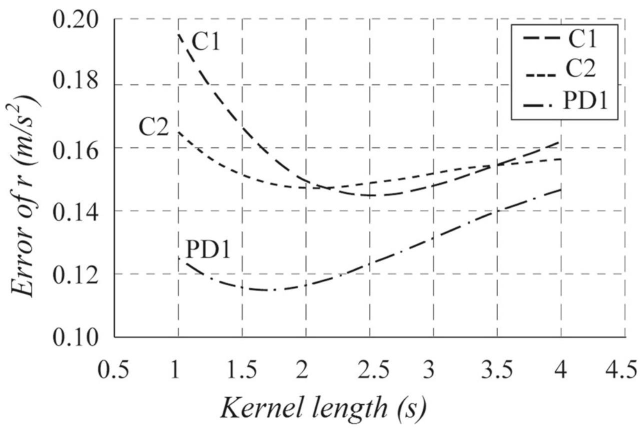

Fig. 3 The error function of three signals: a patient with PD (PD1) and two control subjects (C1 and C2)

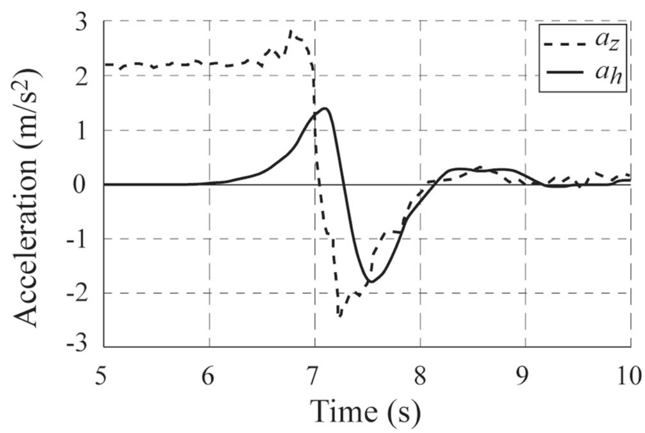

Fig. 4 Relative and absolute acceleration components the Si-St transition of a patient with PD

error function is small, the estimation of the transformation matrix components can be assumed correct. Figure 3 presents three different curves: a patient with PD and two control subjects. The three curves have a minimum error at the time interval of 1.7 and 2.8 s of the kernel's width. The shape of the transformation matrix components depend on the kernel's width [26], subsequently all the acceleration signals were analyzed by using a unique kernel's width of 2.0 s. Additionally, Table 1 shows the output errors of using this kernel's width for all analyzed patients and subjects.

Figure 4 shows the acceleration signal during the Si-St transition of a patient with PD. The dashed line represents the acceleration component referred to the mobile reference z, while the continuous line represents the acceleration component referred to the fixed axis h, this acceleration is calculated from the Eq. 4. This acceleration component is equal to zero until the time that the patient begins to move. The Si-St transition starts at 6.0 s. Later, the transition finalizes approximately at 8.3 s. At that time, a small oscillation around zero is observed, probably due to the standing instability activity. The acceleration component referred to the mobile axis z shows some changes at the 6.5 s. These changes are related to the initial transition phase. At the time of 8.0 s, the α angle decreases and the mobile axis z moves around the horizontal axis h. Consequently, the behavior of both curves present a similar trend.

Figure 5 shows the acceleration a_h, velocity v_h, and the displacement d_h components referred to the fixed reference. The velocity and displacement signal are calculated from the straightforward integration of the acceleration signal. The velocity component presents a local maximum at 7.3 s and a local minimum at 8.3 s. The velocity is equal to zero when the time frame reach at 9.0 s, which means that the standing up and stabilization activity have finished. Additionally, a delay in the onset of the velocity component with respect to the acceleration is noticed. The position signal

Table 1 Output errors when using a kernel's width of 2 s

Parkinson disease		Control subjects	
Patients	Output error (m/s^2)	Subjects	Output error (m/s^2)
PD1	0.098	C1	0.206
PD2	0.164	C2	0.150
PD3	0.106	C3	0.169
PD4	0.135	C4	0.117
PD5	0.115	C5	0.147
PD6	0.112		
PD7	0.145		
PD8	0.094		
PD9	0.114		
PD10	0.127		
Mean	0.121	Mean	0.158
Standard deviation	0.022	Standard deviation	0.033

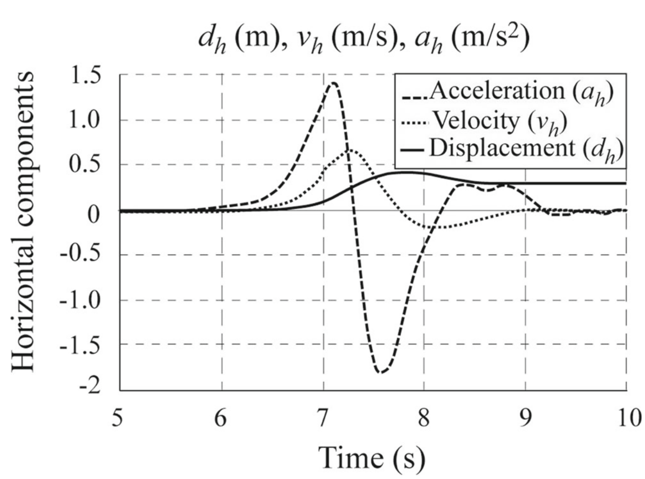

Fig. 5 Acceleration, velocity, and displacement components in the horizontal direction

indicates that the Si-St transition has a maximum displacement of 40 cm in the horizontal direction, but at the end of the activity, the position is stabilized around 30 cm.

3 Results

Once the kinematic data is registered from all the control subjects and patients with PD, it is required to parameterize the Si-St and St-Si transitions. For this purpose, the horizontal components of velocity v_h is chosen to classify the transition phases, because this parameter is easy to comprehend and dispose less noise than the acceleration parameter. Then, the activity transition can be categorized in two phases of movement, the initial phase (IP) and the stabilization phase (SP). The IP begins when the trunk is moving and gaining momentum to lift the buttocks off the chair. This initial activity increases the horizontal component of the velocity till a maximum value. Later, the trunk of the subject slows down until v_h is zero, this particular activity defines the SP. Figure 6 shows the characteristic behavior of v_h during a Si-St (Fig. 6a) or St-Si (Fig. 6b) transitions. It is also illustrated the kinematic parameters that define the movement patterns, such as the duration of the IP (t_{IP}), the duration of the SP (t_{SP}), the total duration of the transition (t_m), the maximum velocity (V_{max}), the minimum velocity (V_{min}), and the velocity ratio (VR), which is defined by the curve's slope that intersects the local maximum and minimum peaks of the velocity signal. The average values of the aforementioned parameter are listed on Table 1.

The variation of t_m depends on the physical conditions of subjects to do the activity. These conditions are inherent to each human being. All the studied subjects were asked to do the Si-St and St-Si transitions as fast as possible. Although the speed is relative and depends on how fast is each subject. For this reason, it is decided to estimate a dimensionless parameter to compare the kinematic signals. This parameter is defined by the quotient between t_{IP} and t_m and is named as the relative duration of the initial phase (t_{IPr}). The temporal parameters t_{IP}, t_{SP}, and t_m are defined from a threshold value which is estimated as a fraction of the total area under the velocity curve. Initially, thresholds of 1, 2, and 5% of the total area were assessed as cutoff values without showing any significant difference in the results. Consequently, a threshold of 1% in both sides of the signal was assumed as the arbitrary cutoff value. In this manner, t_{IP} is defined within the range of the area under the velocity curve equal to 1% until the velocity value is equal to 0. Whereas t_m is defined within the range of the area under the velocity curve between 1 and 99%, which is the same than the addition of the duration of initial and stabilization phases ($t_{IP} + t_{SP}$), as shown in Fig. 6a, b.

Table 2 presents the median values of different kinematic parameters during the Si-St and St-Si transitions. A non-parametric test, the Mann-Whitney U test, is applied to compare the median between control and PD groups, where a p value of 0.05 is considered to be significant. The V_{min} parameter for Si-St and the V_{max} parameter for St-Si are marginally significant, due to the p values of 0.069 and 0.070, respectively. On the contrary, the parameter which define relative duration of the initial phase t_{IPr} is statistically significant, because the p values are 0.006 and 0.011 for Si-St and St-Si transitions, respectively. The rest of the kinematic parameters do not show a statistical significance.

Figure 7 shows a boxplot with the median and the quartiles of the t_{IPr} parameter for Si-St and St-Si transitions. The difference between the control subjects and the patients with PD are presented in both activities. During the Si-St transition, the PD group takes relatively more time at the IP than in the SP. The contrary happens when the St-Si transition is analyzed.

4 Discussion

In this study, the acceleration signal recorded by the triaxial accelerometer presents a deviation from zero. This deviation is due to the accelerometer axes' inclination with respect to the gravity acceleration vector. Then, to estimate the acceleration respect to an absolute reference, it is necessary to use the transformation matrix. Previous studies have used

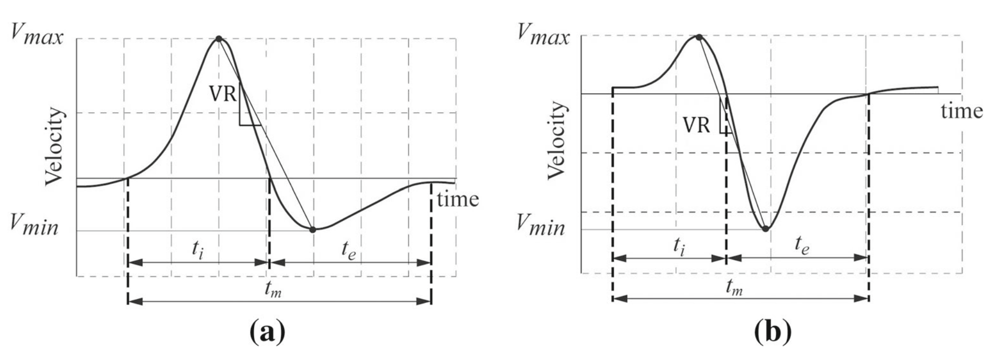

Fig. 6 Characteristic behavior of v_h for **a** Si-St and **b** St-Si transitions

Table 2 Statistical analysis of different kinematic parameters during the Si-St and St-Si transitions

Event	Parameter	Median		Statistic
		Control	PD	*p* value
Si-St	t_{IP} [s]	1.1	1.3	0.391
	t_{SP} [s]	1.6	1.5	0.565
	t_m [s]	2.7	2.8	0.924
	V_{max} [m/s]	0.55	0.50	0.343
	V_{min} [m/s]	– 0.27	– 0.20	0.069
	VR [m/s]	– 1.13	– 0.74	0.164
	t_{IPr} [%]	42.3	48.1	0.006
St-Si	t_{IP} [s]	1.5	1.5	0.771
	t_{SP} [s]	1.2	1.5	0.104
	t_m [s]	2.6	2.9	0.292
	V_{max} [m/s]	0.30	0.21	0.070
	V_{min} [m/s]	– 0.47	– 0.46	0.504
	VR [m/s]	– 0.92	0.58	0.153
	t_{IPr} [%]	54.9	46.4	0.011

this transformation method to convert the acceleration data recorded by a uniaxial [25] or triaxial [27] acelerometers. The inclination is calculated as a function of average of the instantaneous acceleration value. This average value is estimated by using a polynomial fit or a low-pass filter, as was done in the present manuscript. Particularly, a moving average low-pass filter was used with a kernel's width that was optimized in the time domain. The kernel's width affects the shape of the filtered signal, because of changing the peak amplitude of the acceleration signal [26]. Additionally, the optimum kernel's width that minimizes the error function is not the same for all the kinematic signals of the studied subjects. Although a unique kernel's width of 2.0 s was chosen to compare all the subjects. Nevertheless, the authors are aware that the present kinematic analysis is likely to change by using different kernel's widths, but that condition is expected to be addressed in future work.

The acceleration component referred to an inertial system allows to define accurately the beginning of the Si-St transition. Firstly, the acceleration signal is approximately equal to zero because the subjects are not moving. Sometimes, the acceleration is different than zero due to the device is affected by the gravity. This means that the acceleration depends on the accelerometer inclination with respect to the gravity vector. In addition, it is more complex and less intuitive to define when the patient begins to move in a mobile reference as compared to an inertial reference. For this reason, it was necessary to define an acceleration threshold, in order to decide when the subject starts to move. To do that, a relative acceleration parameter is used as an index to define the beginning of the movement, the mobile reference will experience a certain delay with respect to inertial reference, as shown in Fig. 4.

Similar to previous studies [3, 28], the time duration of the Si-St and St-Si transitions do not show significant differences between patients with PD and control subjects. In this sense, the speed to perform these transitions depend on the subject, because the speed is relative to each person accordingly. In this work, a dimensionless parameter, like the relative duration of the initial phase t_{IPr}, is found to differentiate small variations of the time to do the transition. This parameter presents a certain degree of independence with respect to the duration of the entire transition. During the Si-St transition, patients with PD show a higher value of t_{IPr}. This situation can be explained with the greater trunk's flexion found in the patients with PD [3]. Furthermore, when the v_h is nearly zero during the change from IP to SP, it is not associated with a simple motor activity [29]. Then, the t_{IPr} variation by comparing different groups, as shown in Fig. 7, is defined as a sequential alteration which is related to some diseases. In particular, diseases make the subject not capable of achieving sequential tasks. Moreover,

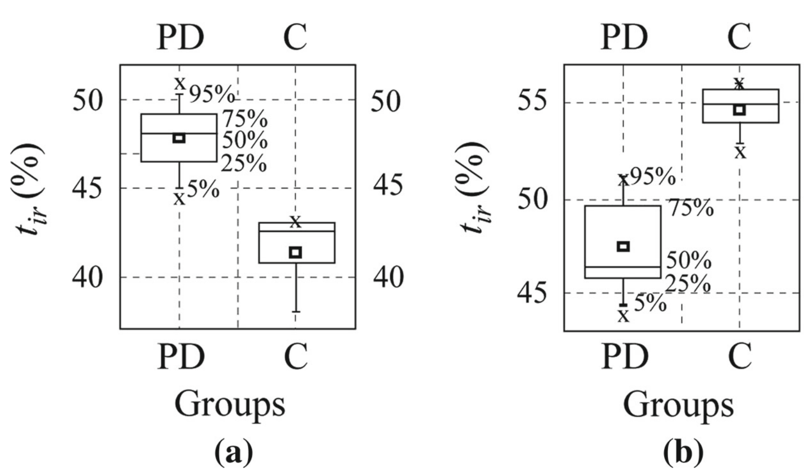

Fig. 7 Boxplot of t_{IPr} during the **a** Si-St and **b** St-Si transitions

the maximum value of v_h during the Si-St transition and the minimum value of v_h during the St-Si transition are both smaller in the patients with PD than in the control subjects, so no significant differences were found. Finally, the patients with PD present a smaller flexion in the hip and ankle dorsiflexion [30]. This could bring some difficulties to begin the Si-St transition and, ultimately, can lead to a lower v_h and a higher t_{IPr}.

The limitations and the future work of this research can be described in three research activities. Firstly, a larger sample of healthy subjects and Parkinson's patients is required to test the diagnostic capabilities of this novel method. To do that, a specific mobile phone app will be developed to record the signal data from the accelerometer and gyroscope, and subsequently, post-processing analysis will be carried out to assess kinematic features to discriminate signal features between PD and control subjects. The second limitation of this study is that the gyroscope signal was not recorded to validate or improve the proposed model with more complex kinematic features. For that reason, further studies should be performed in patients using the gyroscope signal of the smartphone in search of more discriminative features to be combined, like the one found by Raza et al. [31] and Kostikis et al. [32]. Raza and coworkers found that finger tremors of Parkinson's disease can be discriminated with an accuracy of 82.43% from other movement disorders by computing the signal recorded with a triaxial gyroscope. Kostikis and coworkers used the accelerometer and gyroscope signal to quantify a patient's upper limb tremor symptoms, subsequently they use machine learning algorithms to accurately classified 82% of the patients and 90% of the healthy subjects. Finally, a more accurate mathematical model is needed to be developed by implementing complex maneuvers and combining several kinematic features computed from the accelerometer and gyroscope signal, in order to help in differential diagnosis. Therefore, a machine learning algorithm will be proposed to distinguish between healthy and tremor subjects and, ultimately, to try to measure and classify the tremors type and severity (Table 3).

Table 3 List of nomenclature

	Nomenclature
Si-St	Sit-to-stand position
St-Si	Stand-to-sit position
PD	Parkinson disease
MEMS	Micro-electronic mechanical systems
MSD	Motion sensor devices
ET	Essential tremor
TD	Transition duration
BD	Beat decay
AMI	Auto mutual information
IP	Initial phase of the movement
SP	Stabilization phase of the movement
s_p	Sagittal plane
f_p	Frontal plane
l	Length of the moving average filter
N	Number of points
α	Angle with respect to the vertical direction
d_h	Displacement
g	Acceleration of gravity
a	Acceleration component
v	Velocity component
V_{max}	Maximum velocity
V_{min}	Minimum velocity
VR	Velocity ratio
t_{IP}	Duration of the initial phase
t_{SP}	Duration of the stabilization phase
t_m	Total duration of the movement transition
t_{IPr}	Relative duration of the initial phase

5 Conclusions

A smartphone with a triaxial accelerometer was used to recorded acceleration signals. Later, these signals were analyzed to obtain several kinematic parameters that allows to characterize the Si-St and St-Si transitions.

A numerical method is used to select the proper kernel's width of a moving average filter, in order to determine the gravitational constant components which affect the accelerometer axes while recording the Si-St and St-Si transitions.

The absolute velocity of the patient's trunk is estimated during the Si-St and St-Si transitions, when the acceleration signal was recorded by using an smartphone. A dimensionless index of time is successfully identified to characterize the Si-St and St-Si transitions, allowing to differentiate between PD patients and control subjects.

Acknowledgements The authors want to acknowledge the support of the DICYT institution that belongs to the Universidad de Santiago de Chile (USACH). The authors have no other professional and/or financial affiliations that may have biased the article.

References

1. Nuzik S, Lamb R, Vansant A, Hirt S (1986) Sit-to-stand movement pattern-a kinematic study. Phys Ther 66:1708–1713
2. Cadore EL, Izquierdo M (2013) New strategies for the concurrent strength, power, and endurance-training prescription in elderly individuals. J Am Med Dir Assoc 14:623–624

3. Nikfekr E, Kerr K, Attfield S, Playford DE (2002) Trunk movement in parkinson's disease during rising from seated position. Mov Disord 17:274–282
4. Cadore EL, Casas-Herrero A, Zambom-Ferraresi F, Idoate F, Millor N, Gomez M, Rodriguez-Manas L, Izquierdo M (2013) Multicomponent exercises including muscle power training enhance muscle mass, power output, and functional outcomes in institutionalized frail nonagenarians. Age 36:773–785
5. Millor N, Lecumberri P, Gomez M, Martínez-Ramirez A, Izquierdo M (2014) Kinematic parameters to evaluate functional performance of sit-to-stand and stand-to-sit transitions using motion sensor devices: a systematic review. IEEE Trans Neural Syst Rehabil Eng 22:926–936
6. Movement Disorder Society Task Force on Rating Scales for Parkinson's Disease (2003) The unified parkinson's disease rating scale (UPDRS): status and recommendations. Mov Disord 18:738–750
7. Khemlani MM, Carr JH, Crosbie WJ (1999) Muscle synergies and joint linkages in sit-to-stand under two initial foot positions. Clin Biomech 14:236–246
8. Boonstra MC, van der Slikke RMA, Keijsers NLW, van Lummel RC, Malefijt MCD, Verdonschot N (2004) The accuracy of measuring the kinematics of rising from a chair with accelerometers and gyroscopes. J Biomechan 39:354–358
9. Costa J, González-Rojas HA, Valldeoriola F, Gaig C, Tolosa E, Valls-Sole J (2010) Nonlinear dynamic analysis of oscillatory repetitive movements in parkinson's disease and essential tremor. Mov Disord 25:2577–2586
10. Yang SZ, Laudanski A, Li QG (2012) Inertial sensors in estimating walking speed and inclination: an evaluation of sensor error models. Med Biol Eng Comput 50:383–393
11. Weiss A, Herman T, Plotnik M, Brozgol M, Maidan I, Giladi N, Gurevich T, Hausdorff JM (2010) Can an accelerometer enhance the utility of the timed up, go test when evaluating patients with parkinson's disease? Med Eng Phys 32:119–125
12. Mellone S, Tacconi C, Chiari L (2012) Validity of a smartphone-based instrumented timed up and go. Gait Posture 36:163–165
13. Joundi RA, Brittain J-S, Jenkinson N, Green AL, Aziz T (2011) Rapid tremor frequency assessment with the iPhone accelerometer. Parkinsonism Relat Disord 17:288–290
14. Wile SJ, Ranawaya D, Kiss Z (2014) Smart watch accelerometry for analysis and diagnosis of tremor. J Neuroscience Methods 215:1–4
15. Chen PY, Wei SH, Hsieh WL, Cheen JR, Chen LK, Kao CL (2012) Lower limb power rehabilitat. (LLPR) using interactive video game for improvement of balance function in older people. Arch Gerontol Geriatrics 55:677–682
16. Janssen WGM, Bussmann JBJ, Horemans HLD, Stam H. (2008) Validity of accelerometry in assessing the duration of the sit-to-stand movement. Med Biol Eng Comput 46:879–887
17. Najafi B, Aminian K, Loew F, Blanc Y, Robert PA (2002) Measurement of stand-sit and sitstand transitions using a miniature gyroscope and its application in fall risk evaluation in the elderly. IEEE Trans Biomed Eng 49:843–851
18. Farkas Z, Csillik A, Szirmai I, Kamondi A (2006) Asymmetry of tremor intensity and frequency in Parkinson's disease and essential tremor. Parkinsonism Relat Disord 12:49–55
19. Adame ME, Al-Jawad A, Romanovas M, Hobert MA, Maetzler W, Möller K, Manoli Y (2012) TUG Test instrumentation for parkinson's disease patients using inertial sensors and dynamic time warping (DTW). Biomed Eng 57:1071–1074
20. Barrantes S, Sanchez Egea AJ, Gonzalez Rojas HA, Marti MJ, Compta Y, Valldeoriola F, Simo Mezquita E, Tolosa E, Valls-Sole J. (2017) Differential diagnosis between Parkinson's disease and essential tremor using the smartphone's accelerometer. PLoS ONE 12(8):e0183843
21. Salarian A, Horak FB, Zampieri C, Carlson-Kuhta P, Nutt JG, Aminian K (2010) iTUG, a sensitive and reliable measure of mobility. IEEE Trans Neural Syst Rehabil Eng 18:303–310
22. Ganea R, Paraschiv-Ionescu A, Bula C, Rochat S, Aminian K (2011) Multi-parametric evaluation of sit-to-stand and stand-to-sit transitions in elderly people. Med Eng Phys 33:1086–1093
23. Ladin Z, Flowers WC, Messner W (1989) A quantitative comparison of a position measurement system and accelerometry. J Biomechanics 22:295–308
24. Moe-Nilssen R (1998) A new method for evaluating motor control in gait under real-life environmental conditions. Part 1: the instrument. Clin Biomech 13:320–327
25. Moe-Nilssen R, Helbostad JL (2002) Trunk aceelerometry as a measure of balance control during quiet standing. Gait Posture 16:60–68
26. Cali M, Savio FL (2016) Accurate 3d reconstruction of a rubber membrane inflated during a bulge test to evaluate anisotropy. In: Advances on mechanics, design engineering and manufacturing. Springer International Publishing, pp 1221–1231
27. Lugade V, Fortune E, Morrow M, Kaufman K (2014) Validity of using tri-axial accelerometers to measure human movement- Part I: posture and movement detection. Med Eng Phys 36:169–176
28. Zijlstra A, Mancini M, Lindemann U, Chiari L, Zijlstra W (2012) Sit-stand and stand-sit transitions in older adults and patients with Parkinson's disease: event detection based on motion sensors versus force plates. J Neuroeng Rehabil 9:75:1–10
29. Mak M, Levin O, Mizrahi J, Hui-Chan C (2002) Joint torques during sit-to-stand in healthy subjects and people with Parkinson's disease. Clin Biomech 18:197–206
30. Buckley TA, Pitsikoulis C, Hass CJ (2008) Dynamic postural stability during Sit-to-Walk transitions in Parkinson disease patients. Mov Disord 23:1274–1280
31. Raza MA, Chaudry Q, Zaidi SMT (2017) Clinical decision support system for parkinson's disease and related movement disorders. In: IEEE international conference on acoustics, speech and signal processing (ICASSP), 2017. IEEE, pp 1108–1112. 10.1109/ICASSP.2017.7952328
32. Kostikis N, Hristu-Varsakelis D, Arnaoutoglou M, Kotsavasiloglou C. (2015) A smartphone-based tool for assessing parkinsonian hand tremor. IEEE Journal of Biomedical and Health Informatics 19(6):1835–1842

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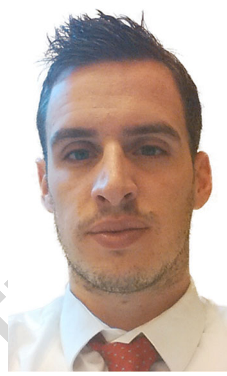

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