Parkinson's Disease Assessment Based on Gait Analysis Using an Innovative RGB-D Camera System

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***Abstract*— Movement-related diseases, such as Parkinson's disease (PD), progressively affect the motor function, many times leading to severe motor impairment and dramatic loss of the patients' quality of life. Human motion analysis techniques can be very useful to support clinical assessment of this type of diseases. In this contribution, we present a RGB-D camera (Microsoft Kinect) system and its evaluation for PD assessment. Based on skeleton data extracted from the gait of three PD patients treated with deep brain stimulation and three control subjects, several gait parameters were computed and analyzed, with the aim of discriminating between non-PD and PD subjects, as well as between two PD states (stimulator ON and OFF). We verified that among the several quantitative gait parameters, the variance of the center shoulder velocity presented the highest discriminative power to distinguish between non-PD, PD ON and PD OFF states (p = 0.004). Furthermore, we have shown that our low-cost portable system can be easily mounted in any hospital environment for evaluating patients' gait. These results demonstrate the potential of using a RGB-D camera as a PD assessment tool.**

I. Introduction

Parkinson's disease (PD) is an idiopathic neurodegenerative disease, which results from the death of brain cells that produce dopamine [1]. The lack of dopamine typically leads to characteristic motor symptoms, such as bradykinesia (i.e. slowness of movement), shuffling gait, and freezing of gait (i.e. sudden and brief motor blocks).

An estimated seven to ten million individuals worldwide have PD [2]. This number is expected to rise significantly in the future [3], with 60,000 new cases being currently reported every year only in the U.S. [2]. Even though PD has presently no cure, there is available treatment that can improve functional capacity. A possible treatment is deep brain stimulation (DBS), which consists in implanting stimulating electrodes in the brain, and a pulse generator.

To provide the best possible treatment, both an early diagnosis and regular evaluations are essential. The diagnosis of PD is currently based mainly on clinical criteria [1]. During PD follow-up, the monitoring of the disease's progression and treatment outcome is usually based on a rating scale, such as the Unified Parkinson Disease Rating Scale (UPDRS) [4]. In both cases, the assessment typically includes visual examination of motor symptoms by physicians, which tends to be rather subjective. So, the quantification of motor signs can be very useful to enhance both PD diagnosis and follow-up [5], [6], and possibly lead to an improvement of treatment and overall life quality of PD patients.

Gait analysis in PD, using motion or vision sensors, has been studied by various authors [5], [6], [7]. In [6], the authors proposed a PD monitoring tool, based on six accelerometers and one gyroscope. Based on sensor data collected from PD patients, they extracted parameters that can be useful for distinguishing between on and off states.

A vision-based system for PD assessment (distinction between non-PD, PD drug on and PD drug off states) was proposed in [5]. The authors recorded videos of PD patients and control subjects while walking. A minimum distance classifier was then built, based on features resulting from gait analysis, which achieved an accuracy of 80.5%.

Recently, the Microsoft Kinect™ has been used for gait analysis [7], [8], [9]. The Kinect is a low-cost, portable RGB-D (Red, Green, Blue, Depth) camera [10] that provides color and depth image sequences, as well as skeleton data resulting from 3D tracking. This camera has the added advantage of being less intrusive than marker-based sensors. Moreover, when compared with RGB cameras, it allows motion analysis in less controlled environments, due to the use of a depth sensor based on infrared light, without losing accuracy [9].

A gait analysis system that uses a Kinect was developed in [8]. Regression models were built based on skeleton data, and ground truth measures (using in-shoe pressure sensors and a gyroscope), which were collected from subjects while walking. The obtained models were able to estimate stride duration and arm angular velocity, with an average absolute error in the range between 32 and 71 milliseconds, and 14 and 22 degrees/second, respectively.

Regarding PD, the validity of the Kinect for movement measurement in PD patients was recently explored in [7]. When compared with a Vicon system, the sensor was able to accurately measure timing and gross spatial characteristics of clinically relevant movements, validating its use for gait analysis in the health care context, namely in PD.

Considering the potential of RGB-D camera systems to constitute a low-cost and portable solution for assessing movement-related diseases, we explore in this contribution

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the possibility of using such a system as a PD assessment tool. We carried out an evaluation of both PD patients and control subjects, during a walking task, which consisted in the extraction of several gait parameters from skeleton data acquired by using our *KinecTracker* application. Moreover, the usefulness of those parameters for supporting both PD diagnosis and follow-up was studied.

II. Materials and Methods

An experimental protocol was carried out in a room at São João University Hospital (Porto, Portugal), with the participation of three PD patients (P1, P2 and P3) and three control subjects (C1, C2 and C3). Each PD patient had an implanted DBS stimulator, and performed the experiment twice: with the stimulator on (STIM ON); and a few minutes after turning off the stimulator (STIM OFF). Each control subject performed the experiment only once.

The protocol included the use of the *KinecTracker* application, developed in C# by our group using the Kinect Software Development Kit v1.5 [11], to acquire skeleton data (at a 30 fps rate) from PD patients and control subjects, while they were walking. The walking trajectory of four meters is illustrated by an arrowed dashed line in Fig. 1. This figure also includes the relevant distances, as well as the Kinect height and tilting angle in relation to the horizontal plane (perpendicular to the gravity force). The chosen setup took into account the Kinect limitations [12], and aimed at maximizing the actual tracking area, which is represented by the grey rectangle in Fig. 1.

The demographics of the control subjects and PD patients are presented in Table I. For the PD patients, disease-related details are shown in Table II, including the number of months since DBS surgery, and the UPDRS scores for the motor examination section and the specific gait item [4]. The study was authorized by the hospital's Ethics Committee, and all subjects signed an informed consent form.

Each acquired frame data corresponds to a skeleton of twenty joints, illustrated in Fig. 2 (a). Fig. 2 (b) shows an example of depth and skeleton data, as displayed in *KinecTracker* (user interface shown in Fig. 3). Each joint corresponds to a 3D position, considering the coordinate system associated with the Kinect [12] (depicted in Fig. 1).

The data acquired within the tracking area were firstly manually selected, and then partitioned into gait cycles, based on depth data acquired at the same time as the skeleton data.

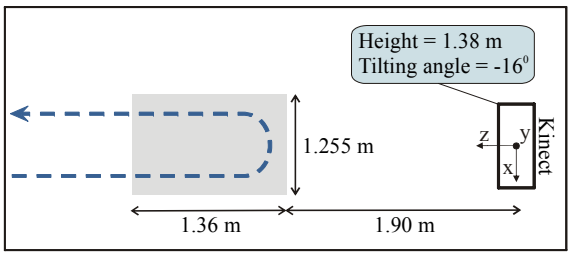


Fig. 1. Experimental setup used for data acquisition, including the coordinate system associated with the Kinect.

TABLE I

Subjects' characterization (average and [minimum, maximum] values for age, weight, and height).

	Control subjects	PD patients
Gender (male/female)	2/1	2/1
Age	49 [46, 54]	53.7 [47, 59]
Height (m)	1.65 [1.58, 1.72]	1.68 [1.59, 1.8]
Weight (kg)	83.3 [54, 118]	82.7 [78, 90]

TABLE II

Parkinson's disease patients' characterization regarding DBS and UPDRS scores.

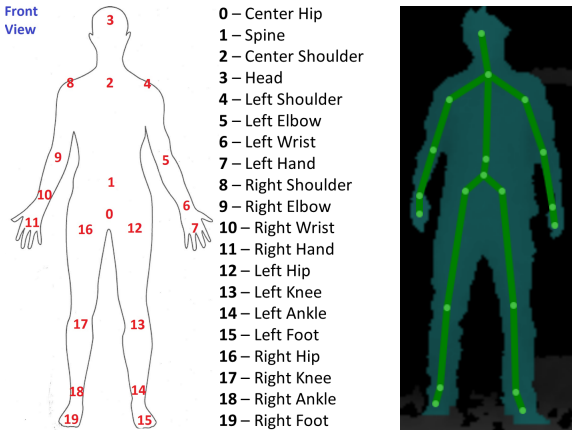
PD patient	Months after DBS surgery	UPDRS III[a] (gait[b])	
		STIM ON	STIM OFF
P1	6	13 (1)	31 (1)
P2	1.5	7 (1)	26 (1)
P3	10	11 (0)	42 (2)

[a] UPDRS motor score (part III). The maximum score is 108. [4]
[b] UPDRS gait sub-score (item 29). Score ranges between 0 (normal) and 4 (cannot walk). [4]

We considered that a gait cycle begins when the left/right foot initiates contact with the ground ($IC_{L/R}$), and ends when the same foot initiates again contact with the ground. In the data analysis presented below, we used only the data corresponding to the portion of the walking sequence where the subject is walking towards the camera, since we verified that the remaining data were much noisier.

As indicated in Fig. 1, the Kinect was tilted by rotating $-16°$ around its x-axis, with the aim of obtaining the optimum field of view. In order to simplify comparison between results obtained with different angles, and facilitate interpretation of results, the joints' 3D positions were converted into a coordinate system corresponding to a non-tilted camera (angle of 0°).

Based on the resulting data we created two different datasets: unfiltered and filtered. The filtered dataset was



(a) (b)

Fig. 2. Skeleton joints provided by the Kinect (a), and depth and skeleton data as displayed in the *KinecTracker* application (b).

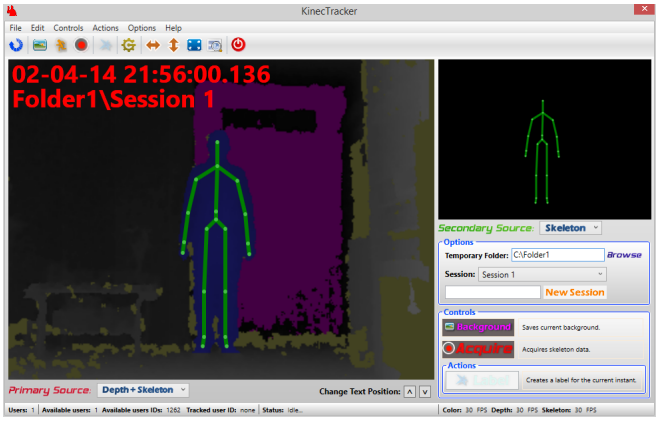


Fig. 3. User interface of the *KinecTracker* application.

obtained by using a first order low-pass Butterworth filter, with a cutoff frequency of 5 Hz, over the unfiltered data. For both datasets, the following 34 measures were computed, for each frame of each left/right gait cycle:

- Velocity of the left/right foot, ankle, knee and hip, right/left hand, wrist, elbow and shoulder, central hip and shoulder, spine, and head, using (1);
- Acceleration of the left/right foot, ankle, knee and hip, right/left hand, wrist, elbow and shoulder, central hip and shoulder, spine, and head, using (2);
- Distance between feet, ankles, knees, hands, wrists, and elbows, using (3);
- Angle at left/right knee (defined by hip, knee and ankle joints), right/left elbow (defined by wrist, elbow and shoulder joints), center shoulder (defined by spine, center shoulder and head joints), and spine (defined by center hip, spine and center shoulder joints), using (4).

$$\text{velocity} = \sqrt{v_x^2 + v_y^2 + v_z^2} \approx \sqrt{\frac{\Delta x^2 + \Delta y^2 + \Delta z^2}{\Delta t^2}} \quad (1)$$

$$\text{acceleration} = \sqrt{a_x^2 + a_y^2 + a_z^2} \approx \sqrt{\frac{\Delta {v_x}^2 + \Delta {v_y}^2 + \Delta {v_z}^2}{\Delta t^2}} \quad (2)$$

$$\text{distance} = \|\overrightarrow{\mathbf{P_{left}}\mathbf{P_{right}}}\| \quad (3)$$

$$\text{angle} = \arccos\left(\frac{\overrightarrow{\mathbf{P_2}\mathbf{P_1}}.\overrightarrow{\mathbf{P_2}\mathbf{P_3}}}{\|\overrightarrow{\mathbf{P_2}\mathbf{P_1}} \times \overrightarrow{\mathbf{P_2}\mathbf{P_3}}\|}\right) \quad (4)$$

In (1), v_x is the component of the velocity vector on the x-axis for a given joint, and Δx corresponds to the difference between the x-coordinate values considering two consecutive frames. In (2), a_x is the component of the acceleration vector on the x-axis for a given joint, and Δv_x refers to the difference between velocities, on the x-axis, considering two consecutive frames. Similar notations are used for the y- and z-axis. In both (1) and (2), Δt is the time elapsed between two consecutive frames.

In (3), $\mathbf{P_{left}}$ and $\mathbf{P_{right}}$ refer to the left and right joint 3D positions, respectively. In (4), $\mathbf{P_1}$, $\mathbf{P_2}$ and $\mathbf{P_3}$ correspond to three different joint 3D positions. For example, considering the angle at left knee, these points correspond to the coordinates of the left hip, knee and ankle joints, respectively.

A set of parameters, for each gait cycle, was then computed over the obtained velocities, accelerations, distances and angles: average, median, variance, and variance divided by the average (normalized variance). This resulted in 136 different parameters.

Additionally, the following four parameters were obtained, for each gait cycle: gait cycle duration, stride length, stride average velocity, and cadence. For the right leg, these parameters were computed using (5), (6), (7) and (8), respectively. In (5) and (6), k corresponds to the gait cycle number. In (6), $\mathbf{P_{IC_R}}(k)$ and $\mathbf{P_{IC_R}}(k+1)$ refer to the right ankle 3D positions at instants $\text{IC}_\text{R}(k)$ and $\text{IC}_\text{R}(k+1)$, respectively. Similar equations were used for the left leg.

$$k\text{th gait cycle duration} = \text{IC}_\text{R}(k+1) - \text{IC}_\text{R}(k) \quad (5)$$

$$k\text{th stride length} = \|\overrightarrow{\mathbf{P_{IC_R}}(k)\mathbf{P_{IC_R}}(k+1)}\| \quad (6)$$

$$\text{stride average velocity} = \text{stride length}/\text{gait cycle duration} \quad (7)$$

$$\text{cadence} = 1/\text{gait cycle duration} \quad (8)$$

III. Results

In order to evaluate which parameters can be used to statistically distinguish between non-PD subjects, PD patients in the STIM ON state and PD patients in the STIM OFF state, we performed the Kruskal-Wallis test [13] for each different parameter. The results ($p < 0.05$) for each dataset (unfiltered and filtered) are presented in Table III, where the lowest value for each case is indicated in bold.

Fig. 4 shows an example of the center shoulder velocity versus the elapsed time, during a single gait cycle carried out by subject C2 and patient P2 in the STIM OFF state, when considering the filtered data. The corresponding variance values are also indicated in Fig. 4.

TABLE III
KRUSKAL-WALLIS TEST RESULTS ($p < 0.05$), WHEN COMPARING NON-PD, PD STIM ON AND PD STIM OFF STATES, FOR THE UNFILTERED AND FILTERED DATASETS.

Parameter			*p*-value[a]	
			Unfiltered	*Filtered*
Variance	Velocity	Head	N.S.	0.011
		Center shoulder	0.027	**0.004**
		Shoulder	N.S.	0.021
	Acceleration	Center shoulder	0.042	0.016
	Distance	Elbows	0.019	0.024
	Angle	Elbow	0.046	N.S.
Normalized variance	Velocity	Elbow	N.S.	0.046
		Center shoulder	**0.009**	0.006
		Shoulder	N.S.	0.039
	Acceleration	Center shoulder	0.041	0.008
	Distance	Elbows	0.024	0.024
Average	Acceleration	Center shoulder	N.S.	0.041
Stride duration			0.045	0.045
Cadence			0.045	0.045

[a] N.S. means non-significant ($p >= 0.05$).

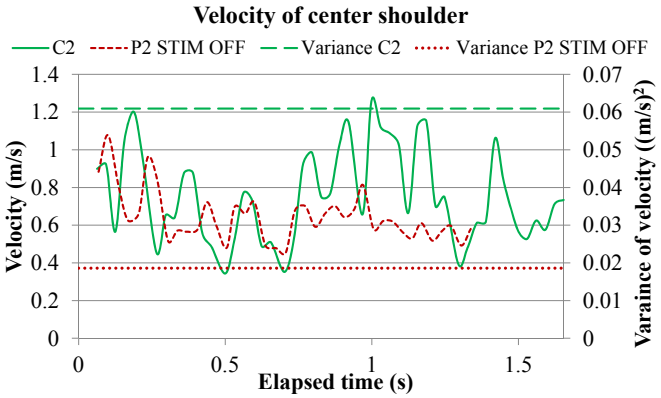


Fig. 4. Velocity of the center shoulder versus the elapsed time, for a gait cycle performed by subject C2 and patient P2 in STIM OFF state, considering the filtered dataset. The associated variance values are also included.

IV. Discussion and Conclusion

In this contribution, we used a system based on a single sensor that minimizes intrusiveness, when compared with the use of several sensors attached to the body in [6]. Similarly to [5], we explored the possibility of both PD diagnosis and follow-up based on gait analysis. However, in contrast with [5], we relied on depth images and skeleton data based on infrared light instead of common RGB images, which allowed a less controlled environment (background color, lighting, and subject clothing). Comparing with [8], we analyzed a greater number of gait parameters, associated with all skeleton joints provided by the Kinect. Moreover, we identified the most appropriate parameter for PD assessment.

From Table III, we can see that filtering contributes to an overall improvement of the parameters' ability to statistically distinguish between three different states: non-PD, PD STIM ON, and PD STIM OFF. It can also be seen that the variance of the center shoulder velocity seems to be the most appropriate parameter for discriminating between the three considered states (p = 0.004). From the example depicted in Fig. 4, we can see that the value of this parameter is smaller for the PD patient, when compared with the control subject. This can be explained by the fact that PD patients tend to walk slower, and therefore their walking speed does not reach values as large as for healthy subjects.

The presented results show the potential of using a low-cost RGB-D camera-based system for supporting both PD diagnosis and follow-up, which can be very important for early detection of PD and treatment outcome improvement. Consequently, it can contribute to an increase of the patients' quality of life, and a reduction of health care costs.

V. Future Work

Although the obtained results provide indications for using RGB-D cameras to support PD assessment, more data are required to confirm these preliminary indications. Acquisition sessions with new subjects are already scheduled and the associated results will be included in the next contribution. Furthermore, we have now integrated the pre-release version of the new Kinect for Windows v2 [14], which is expected to have better overall characteristics, into the *KinecTracker* application. This pre-release camera was awarded to our R&D group as a "Developer Preview Program" member, and will be used in the present system evolution.

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