Comparative and adaptation of step detection and step length estimators to a lateral belt worn accelerometer

Taufique Sayeed, Albert Samà, Andreu Català, Joan Cabestany,
Technical Research Centre for Dependency Care and Autonomous Living (CETpD) Rambla de l'Exposicio, 59-69 08800 Vilanova i la Geltru, Spain.
taufique.sayeed @estudiant.upc.edu, albert.sama@estudiant.upc.edu, andreu.catala@upc.edu, joan.cabestany@upc.edu

Abstract - **Parkinson's Disease (PD) is a neurodegenerative disease that predominantly alter patients' motor performance and compromises the speed, the automaticity and fluidity of natural movements. The patients fluctuate between periods in which they can move almost normally for some hours (ON state) and periods with motor disorders (OFF state). Gait properties are affected by the motor state of a patient: reduced stride length, reduced gait speed, increased stride width etc. The ability to assess the motor states (ON/OFF) on a continuous basis for long time without disturbing the patients' daily life activities is an important component of PD management. An accurate report of motor states could allow clinics to adjust the medication regimen to avoid OFF periods. The real-time monitoring will also allow an online treatment by combining, for instance, with automatic drug-administration pump doses. Many studies have attempted to extract gait properties through a belt-worn single tri-axial accelerometer. In this paper, a user friendly position is proposed to place the accelerometer and three step detection methods and three step length estimators are compared considering the proposed sensor placement in signals obtained from healthy volunteers and PD patients. Adaptation methods to these step length estimators are also proposed and compared. The comparison shows that the adapted estimators improve the performance with the new proposed step detection method and reduce errors in respect of the original methods.**

Keywords— Parkinson disease(PD), step length, gait speed, center of mass (COM)

I. INTRODUCTION

Parkinson's disease is the second most common neurodegenerative disease in the people aged over 40 years. The disease alters patients' motor control, i.e tremor, reduced walking speed, rigidity, muscle stiffness, impaired postural balance etc. Levodopa or similar medication can reduce the motor symptoms of PD patients. After some years of medication, patients will experience fluctuation between ON and OFF periods. ON periods are characterized as the period when the motor symptoms are almost invisible with the exception of Dyskinesia (unvoluntary movements) and the patient feel relatively clear and in control of their movements. OFF state is the period when the motor symptoms are more prominent. Early detection of OFF states are necessary in order to apply prevention strategies in proper time. Moreover motor status detection can help to improve the response to treatment by modifying the medication regimen according to the motor fluctuations.

Relation between gait parameters and motor states has been widely analyzed in the treatment of PD. Reduced stride[1] length and gait speed are common symptoms on PD patients that will be useful for the diagnose of the motor states [2][3]. Recently, some systems using wearable devices with MEMS sensors like accelerometers, gyroscopes and magnetometers have been developed to measure the stride length and gait speed. Their portability and self-administrable methods makes them suitable to be used outside the clinical environment [2][3][4].

Accelerometer data are easy to interpret and less interfering than other sensors, i.e. they barely have drifts due to temperature although drifts appear due to gravity. This is the reason why accelerometers are widely used for continuous gait analysis. Many studies found that positioning the accelerometer on the waist near the joint between the 4th and 5th lumbar vertebrae in the spine (L4-L5) provides then most valuable information for gait analysis than other parts of the body [5][6]. However, Mathie et al [7] showed that this location is impractical to place a device during daily life because it is uncomfortable, may hurt the patient or could be damaged during sitting on a chair or lying on the bed and also needs assistance from other person to find the position and place it in right position. Consequently, they proposed that a different sensor placement above the anterior superior iliac spine (ASIS) could be a better choice. The position is more user friendly and comfortable.

In this work, accelerometer based system is suggested as a potential device placed on the lateral side of waist. It is portable, can be used during daily activities and can also be used to measure the other symptoms of PD. A review of selected methods for step detection, step length and gait speed is given in this study. A new step detection method (SWAT) is also proposed here. These methods are tested in a small database of signals gathered with proposed sensor position on healthy subjects and PD patients. This paper also presents some adaptation to the current step length methods for the new position which results are also presented.

This work is supported by the Personal Health Device for the Remote and Autonomous Management of Parkinson's Disease (REMPARK) project [8]. The aim of this project is to develop a Personal Health care System (PHS) for the improved management of PD. To achieve the goal, a system able to identify the motor status in real time, provide gait guidance system, will be developed. The work presented in this paper will be included as part of the PHS and the data from PD patients that is being gathered under this project [9] has been used in this paper

II. STEP DETECTION METHOD

This section describes 2 step detection methods from the literature and one proposed method. They were applied to the proposed sensor location (lateral side of waist) and compared their performance.

A. Sliding window summing technique(SWS)

Shin et al [10] proposed a method that employs a sliding window summation and acceleration differentials. They calculated the magnitude of acceleration a_i

$$a_i = \sqrt{a_{xi}^2 + a_{yi}^2 + a_{zi}^2} \quad (1)$$

where a_n are the 3D acceleration values at time i towards horizontal. Sliding window summation technique (SWST) was hen implemented using following equation

$$SWST = \sum_{t=i-w+1}^{i} a_t \quad (2)$$

where w is the window size fixed to 0.2s interval. In the experiment, size of w is set 40 as the operating frequency is 200Hz. Noise and effect of gravity were reduced using an acceleration differential technique that is

$$a(k) = SWST(k+w) - SWST(k) \quad (3)$$

Step was detected from the zero crossing points of the jerk signal.

B. Threshold based approach (CETpD)

This method was developed in CETPD lab [2]. In this case, the forward acceleration was filtered by 2nd order low pass Butterworth filter with 15 Hz cut off frequency and the lateral acceleration was filtered by 4th order low pass Butterworth filter with 0.8 Hz cut of frequency.

Mean acceleration $\bar{a}_x$ and standard deviation σ_x are then calculated from the forward acceleration (X). Using $\bar{a}_x$ and σ_x, three thresholds T1, T2 and T3 were set as follows

$$T1 = \bar{a}_x + 0.7 * \sigma_x \quad (4)$$

$$T2 = \bar{a}_x - 0.7 * \sigma_x \quad (5)$$

$$T3 = 10.15 \quad (6)$$

Peaks are detected from the forward acceleration by finding the local maxima values. For each peak greater than T1, local minimum values of lateral acceleration are detected. Steps are identified to start from a local minima of forward acceleration smaller than T2 until another one, while between them the mean magnitude acceleration should be greater than T3.

C. Sliding Window Averaging Technique (SWAT)

This proposed method computes the magnitude of acceleration a_i using Eq (1). The local mean acceleration $\bar{a}_i$ was then computed using the following equation:

$$\bar{a}_i = \frac{1}{w}\sum_{j=1}^{w} a_j \quad (7)$$

In this case, the mean was calculated for each sample using an overlapped sliding window averaging technique (SWAT). The averaging window size was fixed to 40 samples following the same rule as [10].

For this method, the participants were asked to stand still at least 10 seconds before starting the walk. The alignment error and gravity were reduced from mean acceleration value by subtracting the mean value during this standing position as follows.

$$\bar{a}_i = \bar{a}_i - \bar{a}_{i(stand)} \quad (8)$$

Peaks and the mean value from every peak to zero crossing point were then detected. IC of right leg was then selected from one peak value and left initial contact was selected from mean value of next peak to zero value. To avoid false prediction, for each detected steps any peak between next 0.30 seconds were discarded.

III. GAIT SPEED AND STRIDE LENGTH ESTIMATION

This section describes three selected step length and gait speed estimation methods. These methods are selected from 6 common methods based on their performance on the proposed sensor location obtained in a previous study [11]. First 2 methods presented were developed considering the sensor position near L4-L5 position, close to the center of mass (COM) of human body [12]. In method 3, the sensor was placed on the lateral side of waist, the same than our proposed position.

A. Double Pendulum Model

The most common approach to measure the average step length is to consider human gait as an inverted pendulum model [12]. Based on this biomechanical model, Zijlstra et al [12] proposed a relationship between the step length and the vertical displacement of the COM of human body

$$SL_{M1} = 2 \times \sqrt{2hl - h^2} \quad (9)$$

where l denotes for the leg length of individual from the pelvis (near the COM region) to hill and h denotes the vertical displacement of COM during each step. h can be computed as the range of double integration of vertical accelerations between the instants of two consecutive initial contacts of leg (when the foot strikes the ground) in the direction of forward motion.

Gonzalez et al [13] modified the inverted pendulum model considering the forward displacement of the COM as to be related with the inverted pendulum during the swing phase and a second different pendulum during the double stance phase.

This method considers the total step length is the summation of the displacement in both stages as follows:

$$SL_{M2} = SL_{sp} + SL_{dsp} = 2 \times \sqrt{2hl - h^2} + C \times l_{foot} \quad (10)$$

where SL_{sp} and SL_{dsp} are the step length during swing phase and double stance phase, l_{foot} is the length of individual´s foot and C is the proportional constant.

SL_{sp} is calculated following equation (9)) and C was determined by considering that the forward displacement during double stance is proportional to the foot length l_{foot}. C has been fixed as 0.83 by Han et al [14] and 0.67 by Schmid et al. [15] and are presented as estimator $O_{1.1}$ and $O_{1.2}$ using these constants.

B. Weinberg's Algorithm

Weinberg [16] considered the stride length as a function of the difference of maximum and minimum vertical acceleration the vertical displacement of the hip during one step. This method does not need any integration and, thus, avoids the drift error.

The proposed estimation of the step length is:

$$SL_{M2} = K \times \sqrt[4]{a_{max} - a_{min}} \quad (11)$$

where a_{max} and a_{min} are the maximum and minimum magnitude of vertical acceleration during each step and K is the calibrating constant that is measured for each individual based on the ration of mean real and mean anticipated step length of a course of reference during training phase.

$$K = \frac{mean(SL_{real})}{mean(SL_{estimated})} \tag{12}$$

The results from this method are mentioned as O_2.

C. Optimal parameters for Step length

Shin and colleagues [10] estimated the step lengths using optimal parameters based on a linear combination of walking frequency and the variance of the accelerometer signals during one step.

They detected step by SWS. For each detected step the local acceleration variance σ^2 and walking frequency f were calculated using the following equations

$$f = \frac{1}{t_k - t_{k-1}} \tag{13}$$

$$\sigma_k^2 = \frac{1}{n-1}\sum_{k=1}^{n}(a_k - \bar{a})^2 \tag{14}$$

where $\bar{a}$ is the mean acceleration during one step and n is the number of steps.

The step length were then calculated as

$$SL_{M3} = \propto . f + \beta . \sigma^2 + \gamma \tag{15}$$

where α, β are the weights of walking parameters and γ is a constant that are pre-learned. The regression parameter α, β and γ are learned in a training phase. Results of this method are presented as O_3 here.

D. Adapted methods to new sensor location

The first 2 methods were developed considering the sensor position near COM of human body. These methods were tried to adapt to our system located on left lateral side of waist. But the new position imposes new restrictions that that were not considered in the original methods and that must be taken into account. Mainly, left steps are clearer measured than right steps. To adapt these methods to the new sensor position, we proposed the following adaptations [11].

For method A, instead of using a fixed value for C, we propose a user-dependent value that relates the real step length against the predicted one. Then, C is set in a training phase for each individual by using following formula and its estimations are presented as A_1.

$$C = \frac{mean(SL_{real} - SL_{sp})}{l_{foot}} \tag{16}$$

For method B, we adapted the calibration constant for each individual for left step and right step length separately as follows and then estimated the step length which are presented as estimator A_2

$$K_{left} = \frac{mean(SL_{real\_left})}{mean(SL_{estimated\_left})} \tag{17.1}$$

$$K_{right} = \frac{mean(SL_{real\_right})}{mean(SL_{estimated\_right})} \tag{17.2}$$

For estimator O_3, the step length was calculated using the step detection method followed by the authors whereas for estimator A_3 real detected steps from labeled video analysis were used.

IV. EXPERIMENTS

A. Data collection

An inertial system developed by the CETpD laboratory of UPC, Spain is used to obtain the acceleration measurements. The prototype is composed of a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer and are encapsulated in a 98mm x 51mm x 17mm white case.. The operational frequency of the device is 200Hz.

In this study, the sensor is placed in the left lateral side of the body near the anterior superior iliac spine (ASIS). These affix the sensors so that they move with the pelvis, rather than with the surrounding soft tissues.

3 volunteers performed a task that consisted in a straight walk along a 26m long flat corridor. The participants walked along the path at their own “comfortable pace”. Signals obtained from 4 PD patients performing a similar task during both of their ON and OFF states according to [11] have been also analyzed.

A Casio Exlim high speed video camera is used to record the gait events at 200fps. Following the same methodology than [9], the video recording and the movement signals were synchronized by using a fall of sensor event at the beginning and at the end of each video recording.

Before starting the test and video recording, a sticky paper of 0.16 m length was pasted below the knee on the volunteer’s trouser as a reference length. The video was recorded following the subject from left lateral side parallel to the waist

B. Data analysis

The recorded video is analyzed by the open-source sport technical analysis software KINOVEA [17] to measure accurate step length. Step length were measured by drawing a line between two points where the foot initially touches the ground and measure the length.

An application developed under REMPARK project [9] is used to synchronize the video and the movement signals gathered and to label initial contact and foot-off events on the signals. The program enables the labeling of left /right initial contact and toe off manually with the support of video.

V. RESULTS AND DISCUSSION

Table I compares the result from three step detection methods SWS, CETPD and SWAT. The signals are taken from three healthy volunteers (V1, V2 and V3) and also from 4 Parkinson’s patient (P1, P2, P3 and P4) during both OFF and ON states. The positive/negative percentage error shows the over/under estimation by the methods. Error was calculated comparing the time of real initial contact of the healthy persons and presented in table II. The error for missing or over estimated steps was not calculated.

From Table I and II, we can see that the overall performance of SWAT is better than the others. The step recognition rate is better than the others though sometimes it over estimates the steps. Though the mean error of SWS seems less than the provided by the SWAT method, in reality if we look at the absolute error it is always higher for SWS than SWAT, as well as their standard deviation.

TABLE I. OVERALL STEP DETECTION PERFORMANCE FOR 5 VOLUNTEERS AND 5 PD PATIENTS

	#Steps (r)	SWS		CETPD		SWAT	
		#Steps (det)	*Recog. error (%)*	*#Steps (det)*	*Recog. error (%)*	*#Steps (det)*	*Recog. error (%)*
V1	42	43	+2.38	43	+2.38	42	0.00
V2	42	41	-2.38	40	-4.76	42	0.00
V3	48	48	0.00	44	-8.33	49	+2.08
P1-Off	28	29	+3.57	29	+3.57	28	0.00
P1-On	25	24	-4.00	24	-4.00	24	-4.00
P2-Off	20	20	0.00	20	0.00	20	+0.00
P2-On	20	16	-20.00	16	-20.00	17	-15.00
P3-Off	36	40	+11.11	38	+5.56	37	+2.78
P3-On	36	35	-2.78	34	-5.56	35	-2.78
P4-Off	50	49	-2.00	49	-2.00	49	-2.00
P4-On	32	47	+46.88	41	+28.13	39	+21.88

TABLE II. ERROR COMPARISONS BETWEEN 3 METHODS

Method	mean error	mean abs (error)	SD (error)
SWS	-0.0246	0.0500	0.0768
CETPD	-0.2043	0.3586	0.3397
SWAT	0.0369	0.0404	0.0347

Table III compares the anticipated distance estimated against the real distance during test case, i.e. the second part of the walk by the healthy persons, and, additionally, both values for the total walk. Table IV also compares the real and anticipated distance travelled by PD patients both during their ON and OFF stated. The original (O_2) and adaptation (A_2) of Weinberg algorithm was implemented here. Calibration constant K was calculated for each patient on a training phase during their OFF state and implemented in both of their OFF and ON states for patient P1 and P2 and only in ON states for patients P3 and P4. As we did not have the leg length and accurate step length information of the PD patients, the remaining methods could not be tasted.

TABLE III. REAL AND ANTICIPATED DISTANCE ESTIMATED BY THE ORIGINAL (O_N) AND THEIR ADAPTED (A_N) METHODS FOR 3 HEALTHY PERSONS

	Real	$O_{1.1}$	$O_{1.2}$	A_1	O_2	A_2	O_3	A_3
V1	12.20	12.22	11.28	12.61	12.85	12.81	11.87	11.96
V2	11.76	9.50	8.59	11.98	12.18	12.21	11.97	11.96
V3	11.61	16.04	11.96	10.37	12.54	12.57	13.56	12.42

TABLE IV. REAL AND ANTICIPATED DISTANCE ESTIMATED BY THE ORIGINAL (O_2) AND THEIR ADAPTED (A_2) METHOD FOR 4 PD PATIENTS

Subjects	Real (m)	O_2		A_2	
		Est.(m)	*error (%)*	*Est.(m)*	*error (%)*
P1-Off	15	15.42	+2.81	15.40	+2.67
P1-ON	15	14.65	-2.30	14.82	-1.21
P2-Off	15	14.95	-0.31	14.95	-0.31
P2-ON	15	12.89	-14.08	17.53	+16.87
P3-Off	15.9	15.9	0.00	15.9	0.00
P3-ON	15.75	14.94	-5.16	15.07	-4.32
P4-Off	18.25	18.25	0.00	18.25	0.00
P4-ON	18.2	14.87	-18.32	14.92	-18.02

Table V and VII show a comparison between real and anticipated average step lengths and average gait speeds of the healthy persons, respectively, measured by means of the estimators during the test phase. Standard error of each method were also calculated using Root Mean Square Error (RMSE) and Standard Deviation (SD), which are showed together as RMSE (SD) in the tables. Estimators $O_{1.1}$, $O_{1.2}$, O_2 and O_3 follow the original algorithm for the new sensor location. On the other hand, A_1, A_2, and A_3, follow the proposed adaptation methods.

Table VI also shows a comparison between real and anticipated average step lengths of PD patients using only method O_2 and A_2.

Results show that all the original methods have a tendency to over-estimate the step length as well as gait speed and distances. $O_{1.1}$ and $O_{1.2}$ provides inconsistent results i.e overestimate for one subject and under-estimate for the others. O_6 provide very good and consistent results i.e low SD and O_3 and O_6 has the highest performance.

TABLE V. REAL AND ANTICIPATED AVERAGE STEP LENGTH DURING TEST PHASE OF HEALTHY PERSONS

Sub.		Real	$O_{1.1}$	$O_{1.2}$	A_1	O_2	A_2	O_3	A_3
V1	Dist(m)	0.64	0.64	0.59	0.66	0.68	0.67	0.62	0.63
	RMSE (SD)		0.0960 (0.9730)	0.1076 (0.0973)	0.0706 (0.1092)	0.0561 (0.0445)	0.0514 (0.0401)	0.0296 (0.0242)	0.0266 (0.0246)
V2	Dist(m)	0.62	0.50	0.45	0.63	0.64	0.64	0.63	0.63
	RMSE (SD)		0.1403 (0.0773)	0.1827 (0.0773)	0.0394 (0.1999)	0.0382 (0.0309)	0.0386 (0.0302)	0.0232 (0.0212)	0.0232 (0.0211)
V3	Dist(m)	0.53	0.73	0.54	0.48	0.57	0.57	0.57	0.53
	RMSE (SD)		0.3033 (0.2280)	0.0597 (0.0607)	0.2261 (0.2253)	0.4508 (0.1620)	0.0579 (0.0379)	0.0499 (0.0325)	0.0495 (0.0332)

It is seemed that the both adaptation method A_1 and A_3, performs better both for average step length and speed than their original methods O_1 and O_3.

TABLE VI. REAL AND ANTICIPATED AVERAGE STEP LENGTH DURING TEST PHASE OF PD PATIENTS

Subjects	Real (m)	O_2		A_2	
		Est.(m)	*error (%)*	*Est.(m)*	*error (%)*
P1-Off	0.5357	0.5507	2.80	0.5500	2.67
P1-ON	0.6250	0.6104	-2.33	0.6175	-1.20
P2-Off	0.7500	0.7475	-0.33	0.7475	-0.33
P2-ON	0.8824	0.7582	-14.07	1.0312	16.87
P3-Off	0.4297	0.4297	0.00	0.4297	0.00
P3-ON	0.4500	0.4269	-5.14	0.4306	-4.32
P4-Off	0.3724	0.3724	0.00	0.3724	0.00
P4-ON	0.4667	0.3813	-18.30	0.3826	-18.02

Regarding the adaptation method $A_{2,}$ the average step length and speed are the same as its original method O_2. However, considering the variability between left leg and right leg by using a separated calibrating constant for each leg (Eq. 20.1, 20.2), the errors, both RMSE and SD, are significantly reduced. A_1 provides consistent result with better performance than its original methods. The reason is that in the original method, a fixed proportional constant C was considered. In our case, method A_2, C is calculated for every subject with the proposed adaptation method and, thus, the performance is improved.

TABLE VII. REAL AND ANTICIPATED AVERAGE GAIT SPEED DURING TEST PHASE

Sub.		Real	$O_{1.1}$	$O_{1.2}$	A_1	O_2	A_2	O_3	A_3
V1	Dist(m)	1.10	1.10	1.02	1.14	1.16	1.15	1.07	1.08
	RMSE (SD)		0.1369 (0.1398)	0.1620 (0.1406)	0.0960 (0.1731)	0.1129 (0.0963)	0.0846 (0.0648)	0.0507 (0.0414)	0.0455 (0.419)
V2	Dist(m)	1.21	0.98	0.89	1.24	1.26	1.26	1.23	1.23
	RMSE (SD)		0.2813 (0.1672)	0.3618 (0.1658)	0.0570 (0.3862)	0.0706 (0.0541)	0.1000 (0.0862)	0.0434 (0.395)	0.0436 (0.0539)
V3	Dist(m)	0.87	1.22	0.90	0.80	0.95	0.95	0.93	0.87
	RMSE (SD)		0.5418 (0.4144)	0.1234 (0.1225)	0.3875 (0.3881)	0.1827 (0.1636)	0.1149 (0.0819)	0.0813 (0.0527)	0.0805 (0.0539)

The adapted methods A_1 and A_2 show significant improvement in their performance through a significant reduction in the RMSE and SD. But still they have the tendency to overestimate. With the reduced error and improved result, we found that performance of the proposed method A_3 is the closest to the real value.

VI. CONCLUSION

In this study, 3 different methods for step detection were selected to check their performance in the new sensor location consisting in the lateral side of the waist. Among them, SWAT method performed better than the others. This step detection method was used for 3 selected step length estimators from literature. Adaptation methods for each of the estimators were also developed to adjust them to the new sensor location. The original and the adapted methods were compared with real data from both healthy volunteers and PD patients. Considering the RMSE values and also stander deviation, it was found that the adaptation methods A_1, A_2 and A_3 performed better than the original methods O_1, O_2 and O_3 for healthy persons. The obtained percentage error in the adapted estimator A_2 for PD patients also showed an improved performance in respect of its original method O_2. Estimators A_1 and A_2 show very similar performances and, among them, A_2 has the lowest error. Method O_3 and A_3 provide the closest results to the real data with lowest error. Their low RMS and SD values also show a good significance of their accuracy. Method 3 estimates gait speed and step length with the lowest error and shows that an improvement of step detection in method O_3 can enhance its performance and can provide the best performance.

In this preliminary study, it is concluded that A_1, A_2, O_3 and A_3 are those methods that are going to be further explored and a final method is going to be generated. That method will be tested in the whole REMPARK database, that will be composed of data from 90 PD patients and will be finished before November 2013[8].

ACKNOWLEDGEMENTS

This work was supported in part by the Erasmus Mundus Joint Doctorate in Interactive and Cognitive Environments, which is funded by the EACEA Agency of the European Commission under EMJD ICE FPA nº 2010-0012. This work has been performed in the framework of the FP7 project REMPARK ICT-287677, which is funded by the European Community. The author(s) would like to acknowledge the contributions of their colleagues from REMPARK Consortium.

REFERENCES

[1] A. Salarian, H. Russmann, F. J. G. Vingerhoets, C. Dehollain, Y. Blanc, P. R. Burkhard, and K. Aminian, "Gait assessment in Parkinson's disease: toward an ambulatory system for long-term monitoring.," *IEEE transactions on bio-medical engineering*, vol. 51, no. 8, pp. 1434–43, Aug. 2004.

[2] A. Sama, C. Perez-Lopez, J. Romagosa, D. Rodriguez-Martin, A. Catala, J. Cabestany, D. A. Perez-Martinez, and A. Rodriguez-Molinero, "Dyskinesia and motor state detection in Parkinson's Disease patients with a single movement sensor," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, 2012, pp. 1194–1197.

[3] J. D. Schaafsma, N. Giladi, Y. Balash, A. L. Bartels, T. Gurevich, and J. M. Hausdorff, "Gait dynamics in Parkinson's disease: relationship to Parkinsonian features, falls and response to levodopa," *Journal of the neurological sciences*, vol. 212, no. 1, pp. 47–53, 2003.

[4] B. Kostek, K. Kaszuba, P. Zwan, P. Robowski, and J. Slawek, "Automatic assessment of the motor state of the Parkinson's disease patient--a case study," *Diagnostic Pathology*, vol. 7, no. 1, p. 18, 2012.

[5] F. Bugané, M. G. Benedetti, G. Casadio, S. Attala, F. Biagi, M. Manca, and a Leardini, "Estimation of spatial-temporal gait parameters in level walking based on a single accelerometer: validation on normal subjects by standard gait analysis.," *Computer methods and programs in biomedicine*, vol. 108, no. 1, pp. 129–37, Oct. 2012.

[6] E. Martin, V. Shia, and R. Bajcsy, "Determination of a Patient's Speed and Stride Length Minimizing Hardware Requirements," in *Body Sensor Networks (BSN), 2011 International Conference on*, 2011, pp. 144–149.

[7] M. J. Mathie, J. Basilakis, and B. G. Celler, "A system for monitoring posture and physical activity using accelerometers," *Engineering in Medicine and Biology Society, 2001. Proceedings of the 23rd Annual International Conference of the IEEE*, vol. 4, pp. 3654–3657, 2001.

[8] REMPARK, "About the project," 2013. [Online]. Available: http://www.rempark.eu/. [Accessed: 12-Apr-2013].

[9] A. Samà, C. Perez, D. Rodriguez-Martin, J. Cabestany, J. M. Moreno Aróstegui, and A. Rodríguez-Molinero, "A Heterogeneous Database for Movement Knowledge Extraction in Parkinson's Disease," in *European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning*, 2013.

[10] S. H. Shin and C. G. Park, "Adaptive step length estimation algorithm using optimal parameters and movement status awareness.," *Medical engineering & physics*, vol. 33, no. 9, pp. 1064–71, Nov. 2011.

[11] T. Sayeed, A. Samà, A. Català, and J. Cabestany, "Comparison and adaptation of step length and gait speed estimators from single belt worn accelerometer positioned on lateral side of the body," in *8th IEEE International Symposium on Intelligent Signal Processing*, 2013, p. (Selected for publication).

[12] W. Zijlstra and A. L. Hof, "Displacement of the pelvis during human walking: experimental data and model predictions," *Gait & posture*, vol. 6, no. 3, pp. 249–262, 1997.

[13] R. C. González, D. Alvarez, A. M. López, and J. C. Alvarez., "Modified pendulum model for mean step length estimation," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE.*, 2007, vol. 2007, pp. 1371–4.

[14] T. R. Han, N. J. Paik, and M. S. Im, "Quantification of the path of center of pressure (COP) using an F-scan in-shoe transducer.," *Gait & posture*, vol. 10, no. 3, pp. 248–54, Dec. 1999.

[15] M. Schmid, G. Beltrami, D. Zambarbieri, and G. Verni, "Centre of pressure displacements in trans-femoral amputees during gait.," *Gait & posture*, vol. 21, no. 3, pp. 255–62, Apr. 2005.

[16] H. Weinberg, "Using the ADXL202 in pedometer and personal navigation applications," *Analog Devices AN-602 application note*, 2002.

[17] "Kinovea, A microscope for your videos." [Online]. Available: http://www.kinovea.org/. [Accessed: 12-Apr-2013].