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Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Short communication

Validation of an ambient system for the measurement of gait parameters

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ARTICLE INFO

Article history:

Accepted 14 January 2018

Keywords:

Gait analysis
Spatio-temporal parameters measurement
Elderly people
Depth camera
Fall prevention

ABSTRACT

Fall risk in elderly people is usually assessed using clinical tests. These tests consist in a subjective evaluation of gait performed by healthcare professionals, most of the time shortly after the first fall occurrence. We propose to complement this one-time, subjective evaluation, by a more quantitative analysis of the gait pattern using a Microsoft Kinect. To evaluate the potential of the Kinect sensor for such a quantitative gait analysis, we benchmarked its performance against that of a gold-standard motion capture system, namely the OptiTrack. The “Kinect” analysis relied on a home-made algorithm specifically developed for this sensor, whereas the OptiTrack analysis relied on the “built-in” OptiTrack algorithm. We measured different gait parameters as step length, step duration, cadence, and gait speed in twenty-five subjects, and compared the results respectively provided by the Kinect and OptiTrack systems. These comparisons were performed using Bland-Altman plot (95% bias and limits of agreement), percentage error, Spearman's correlation coefficient, concordance correlation coefficient and intra-class correlation. The agreement between the measurements made with the two motion capture systems was very high, demonstrating that associated with the right algorithm, the Kinect is a very reliable and valuable tool to analyze gait. Importantly, the measured spatio-temporal parameters varied significantly between age groups, step length and gait speed proving the most effective discriminating parameters. Kinect-monitoring and quantitative gait pattern analysis could therefore be routinely used to complete subjective clinical evaluation in order to improve fall risk assessment during rehabilitation.

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1. Introduction

Falls in elderly people very often have dramatic consequences, such as fractures, trauma, hospitalization, or even death ([World Health Organization, 2008](#)). Most of these falls result from established impairments of gait and balance stability. Devices quantifying gait and balance, such as force platforms, motion capture systems, or actimetric carpets, exist. However, they are often costly, and they require time and space to be set up, which considerably limit their use for clinical testing. We think that providing an automatic and efficient quantitative method coupled to a simple motion capture system would allow healthcare professionals to circumvent this limitation. In line with this, we propose a system based on the Microsoft Kinect, a low cost and non-intrusive ambient sensor, to extract gait parameters identified in the geriatric literature as the most relevant to assess fall risk ([Hausdorff et al., 2001](#); [Auvinet et al., 2003](#); [Studenski et al., 2003](#)).

Several studies showed that the Kinect is accurate to extract spatiotemporal parameters (see [Springer and Yogev Seligmann, 2016](#) for a review), and thereby well-suited for gait assessment. Some studies compared the Kinect with a marker-based three-dimensional motion analysis (by using one Kinect version 1 sensor: [Chang et al., 2012](#); [Clark et al., 2013](#); [Stone and Skubic, 2011](#); [Xu et al., 2015](#); [Galna et al., 2014](#); four Kinect v2: [Geerse et al., 2015](#); one Kinect v2 [Mentiplay et al., 2015](#); one Kinect v2 and markers [Ye et al., 2016](#)). Regarding marker-less systems, [Gabel et al. \(2012\)](#) compared Kinect v1 with pressure sensors placed inside the shoe, whereas other authors compared the Kinect v1 to an actimetric carpet ([Motiian et al., 2015](#); [Baldewijns et al., 2014](#)).

Here we compared gait parameters extracted using a single Kinect sensor with those extracted using a twelve cameras OptiTrack system as reference. We also assessed which gait parameters differed significantly between age groups, because those were likely the best predictors of fall risk ([World Health Organization, 2008](#); [Gryfe et al., 1977](#); [Lord et al., 2001](#)). All above-mentioned studies, and more generally most of the studies on gait analysis with the Kinect sensor are based on the Microsoft SDK (with the exception of [Stone and Skubic Stone and Skubic, 2011](#)). We relied

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instead on an algorithm developed by Dubois and Charpillet (2017). The reason was that an accurate representation of the skeleton and the body segments is not necessary to extract the spatio-temporal parameters of gait. In our study, the parameters were extracted from the vertical displacement of the geometric center of the body. This approach has two main advantages. First, parameters can be extracted even if the feet of the walking person are occluded, which is likely to occur in a furnished room. Second, the performance of the analysis is relatively unaffected by the angle of view of the sensor.

2. Method

Participants of three different age groups participated in the experiment: eight young individuals (five women, three men) aged 23–28 (mean = 25 years), nine older participants (five women, four men) aged 67–73 (mean = 69 years), whose gait is often considered as “normal”, and eight senior individuals (five women, three men) aged 76 to 89 (mean = 81 years) who are potentially more affected by “abnormal” modifications of the gait pattern (Gryfe et al., 1977). Additional information regarding the participants is provided in Table S1 in the supplementary materials. The study was conducted in accordance with the Declaration of Helsinki and approved by the local ethics committee.

The experiment took place in a 6 m × 8 m room equipped with twelve OptiTrack cameras (Prime 17 W model) and a single Kinect v2 sensor. The participants wore a suit with 41 reflective markers for the OptiTrack system and walked perpendicularly to and at a distance of 4 m from the Kinect sensor. Subjects performed ten back and forth gait trials at a comfortable speed. At the beginning of each sequence, participants raised the arm in order for the experimenter to synchronize the two systems.

Our processing method was only based on the depth images provided by the Kinect sensor. From the depth information, we extracted the silhouette of the walker using the background subtraction method. The trajectory of the centroid along the vertical axis was used to calculate the different gait parameters as described in Dubois and Charpillet (2017). Regarding the OptiTrack

Table 2

Bland-Altman bias (limits of agreement), and percentage error (PE) (computed as $100 \times (2 \text{ SD of bias}) / ((\text{Mean}_{\text{Kinect}} + \text{Mean}_{\text{OptiTrack}}) / 2)$) for the two systems.

	Bias (95 % LoA)	PE (%)
Step length (cm)	1.95 (−2.10 to 6.01)	6.28
Step duration (s)	−0.003 (−0.044 to 0.039)	7.17
Cadence (step/s)	0.000 (−0.124 to 0.124)	7.05
Gait speed (cm/s)	4.00 (−6.134 to 14.145)	8.96

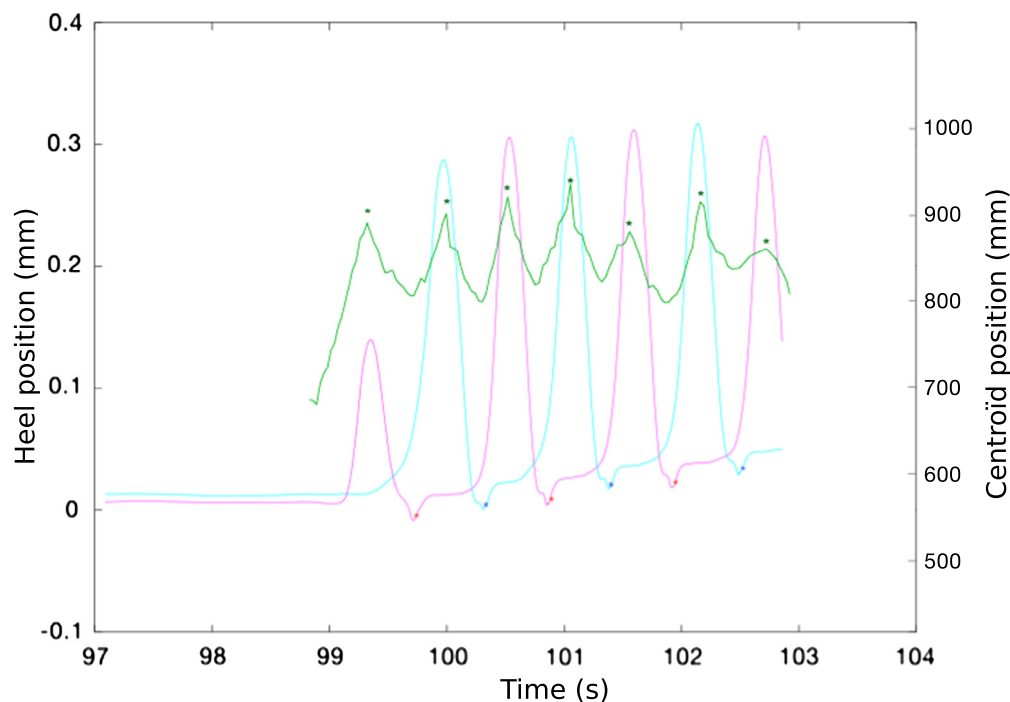


Fig. 1. Trajectories extracted with the Kinect and OptiTrack system during a walking sequence. The green line represents the Kinect centroid along the vertical axis, with green stars indicating the local maxima. The pink and blue lines represent the trajectories of the right and left heel, respectively, as measured by the OptiTrack system. The local minima are represented by the pink and blue stars. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1

Gait parameters and their method of estimation using the OptiTrack and Kinect system.

Variables	OptiTrack	Kinect
Step length (cm)	The distance between the local minima of the left and right heel	The distance between two local maxima
Step duration (s)	The duration between the local minima of the left and right heel	The duration between two local maxima
Cadence (step/s)	1 divided by step duration	1 divided by step duration
Gait speed (cm/s)	Sum of the step lengths divided by the sum of step durations	Sum of step lengths divided by the sum of step durations

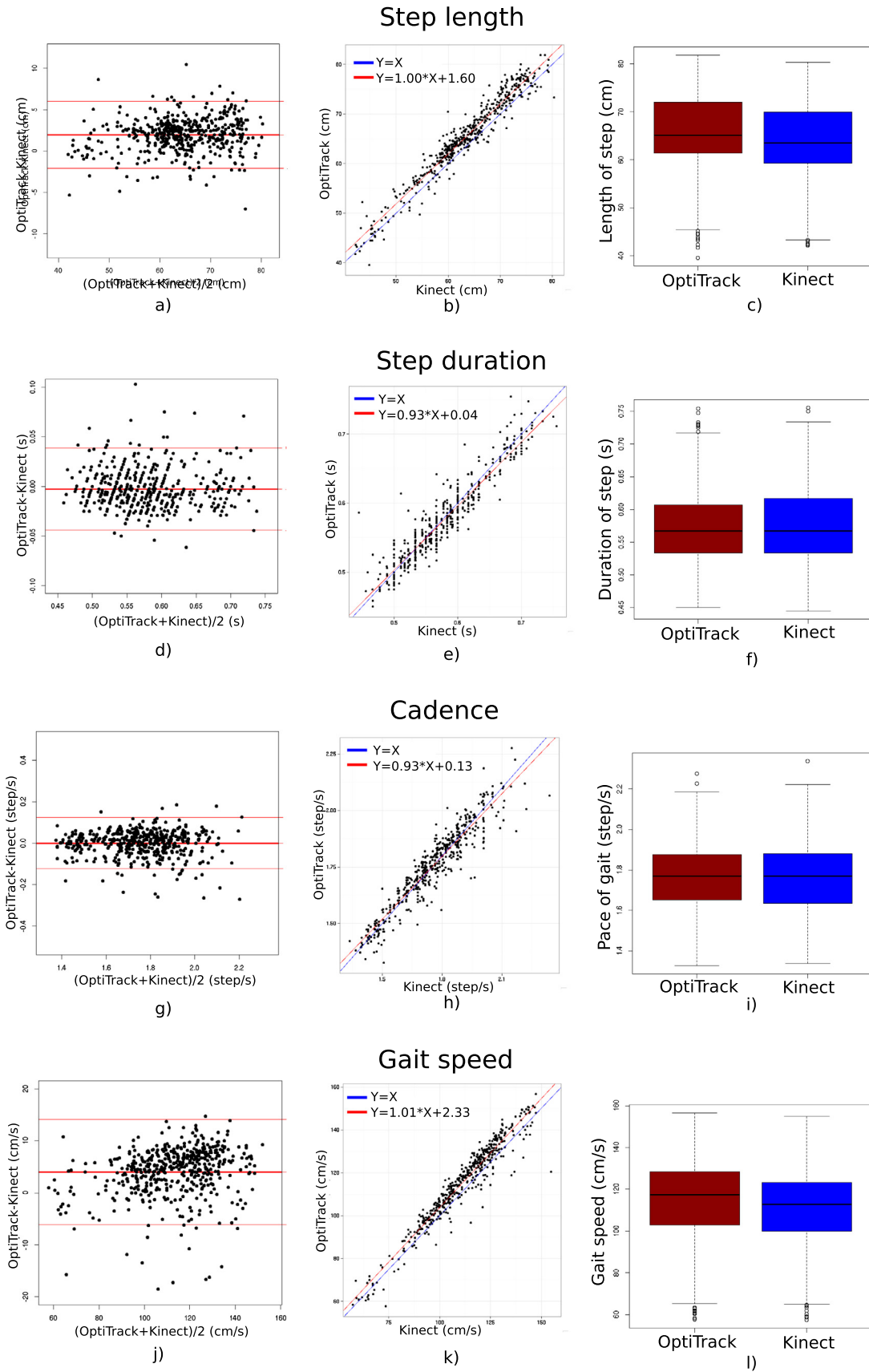


Fig. 2. Different representations of the gait parameters. (a, d, g and j) Bland and Altman plots with 20 values by subject, corresponding to the 20 walking sequences performed by each subject. (b, e, h and k) Scatter plots including all data, with the red line indicating the identity line and the blue line corresponding to the linear best-fit. (c, f, i and l) Boxplots showing the median and variability of the recorded data. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

system, we estimated the parameters using the heel marker trajectory. Fig. 1 shows an example of vertical trajectory extracted by the Kinect sensor as well as the trajectory of the OptiTrack markers. Table 1 shows how and which spatio-temporal gait parameters were estimated. Supplementary Fig. S2 illustrates how step length was estimated by each system. The analysis was performed on steady gait by removing the first step.

Each walking sequence was composed of about 4–6 steps, depending on the participant. Gait parameters were averaged for each walking sequence (each forth and each back lap). Ten sequences were recorded for each participant, for a total of 20 values for each gait parameter and each motion capture system.

The level of agreement between the Kinect and OptiTrack systems was assessed using Bland-Altman 95% bias and limits of agreement (LoA), percentage error (PE), Spearman's correlation, concordance correlation coefficient (CCC), intra-class correlation (ICC) and linear regression. The Bland-Altman analysis was adjusted for repeated measurements in a random-effects model (Carstensen et al., 2008). The PE was calculated by dividing the limits of agreement by the mean of the values obtained with the two systems (Critchley and Critchley, 1999). A bootstrap-method (with 2000 resamples) using bias corrected and accelerated was used to estimate the 95% confidence interval of Spearman's correlation. The CCC, adjusted for repeated measures (Carrasco et al., 2013), assessed the precision and deviation of data from the line of identity. The ICC (Shrout and Fleiss, 1979) was used to assess absolute agreement. Slope and goodness of fit were computed using linear regression. In addition, for each spatio-temporal parameter, differences between age groups were assessed using Kruskal-Wallis tests (non-parametric data) and associated post hoc tests, all Bonferroni-corrected for multiple comparisons. The normal distribution of the data was tested using the Shapiro-Wilk test and variance homogeneity was tested with the Levene test.

3. Results

Table 2 shows the mean difference (bias) and the LoA (mean differences ± 2 SD) between the gait parameters estimated with the two systems. For temporal parameters, the two systems provided very similar values (difference of -0.003 s for step duration and 0.000 step/s for cadence). The Kinect system tended to provide smaller step length (1.95 cm) and gait speed (4.00 cm/s) values. With 500 measured data points, the LoA ranged from -0.044 to 0.039 for step duration, -0.124 to 0.124 for cadence, -2.10 to

6.01 for step length, and -6.134 to 14.145 for gait speed. Moreover, as shown in Fig. 2(a), (d), (g) and (j), most points are within the interval given by the LoA. The 95% confidence interval is not reported here because the data was not normally distributed. Finally, the PE was less than 9% for each parameter, indicating an excellent correspondence between the values provided by the two systems.

Table 3 shows that all correlation values are above 0.92. Since the maximum (absolute) value is 1 (perfect correlation), and a value of 0.70 or higher is considered a strong correlation, our results indicate a very high level of agreement between the two systems for all gait parameters. Fig. 2(b), (e), (h) and (k) show the data recorded with the two systems and a comparison between the identity line and the linear best-fit. The slope of the regression line was very close to 1 for all gait parameters, indicating an excellent correspondence (almost one-to-one) between the data provided by the two systems.

For all four Kinect-extracted gait parameters, the Kruskal-Wallis test indicated a significant difference between age groups ($p < 0.001$ for all four tests). Post-hoc comparisons indicated that for all four parameters, the measured values were significantly different between the young and the senior participants (76–89). However, a significant difference between participants aged 67–73 and participants aged 76–89 could be observed only for step length and gait speed, but not for step duration and cadence. The exact same pattern was observed for OptiTrack-extracted gait parameters. Table 4 shows that the oldest age group had the smallest step length and the slowest gait speed.

4. Discussion

We measured a set of gait parameters routinely used in geriatric screening to assess fall risk. These parameters were extracted using two motion capture systems: the inexpensive, easy to set up, quick to master, and portable Kinect sensor, and the much more expensive and much less convenient to use Optitrack system, which is used in some clinics and is considered a reference system. Using six different methods of comparison, we showed a very high level of agreement between the parameters extracted by the two systems. Our study encompassed a large range of ages, with people aged 23 to 89 years old. Yet, we showed that the Kinect sensor coupled to our algorithm can successfully extract spatio-temporal gait parameters with the same accuracy for all age groups. This is an important result because in the literature, few studies attempted to automatically measure gait parameters with elderly people. And these few studies were usually performed with elderly people affected by health disabilities (Galna et al., 2014).

Below, we compare the results obtained in the current study with those previously reported in the literature. Dubois and Charpillat (2017) compared the gait parameters extracted with a Kinect v1 to those measured with an actimetric carpet. Their study was performed with young individuals, and they extracted the same gait parameters as in the current study, using the same algorithm. However, step durations measured in the current study were more accurate, with a difference of only 0.003 s between

Table 3

Agreement for each parameter as computed with Spearman correlation (95% confidence intervals), concordance correlation coefficient (CCC) and intra-class correlation (ICC) analysis.

	Spearman (Intervals)	CCC	ICC
Step length	0.97 (0.96–0.97)	0.92	0.97
Step duration	0.93 (0.90–0.94)	0.94	0.94
Cadence	0.94 (0.92–0.95)	0.94	0.94
Gait speed	0.96 (0.95–0.97)	0.94	0.96

Table 4

Gait parameter statistics: mean (SD) of 500 values (20 by subjects) obtained for the OptiTrack and Kinect system.

	Global		23–28		67–73		76–89	
	OptiTrack	Kinect	OptiTrack	Kinect	OptiTrack	Kinect	OptiTrack	Kinect
Step length (cm)	65.45 (8.25)	63.50 (7.96)	69.12 (6.54)	67.14 (6.37)	66.78 (5.63)	64.86 (5.41)	60.06 (9.80)	58.09 (9.23)
Step duration (s)	0.576 (0.060)	0.579 (0.061)	0.588 (0.058)	0.590 (0.058)	0.548 (0.046)	0.550 (0.047)	0.600 (0.062)	0.604 (0.064)
Cadence (step/s)	1.76 (0.175)	1.76 (0.177)	1.720 (0.167)	1.718 (0.165)	1.842 (0.151)	1.844 (0.155)	1.686 (0.167)	1.686 (0.171)
Gait speed (cm/s)	114.90 (18.75)	110.90 (17.79)	118.75 (16.05)	114.76 (14.80)	122.66 (14.79)	118.79 (14.54)	101.10 (18.36)	96.93 (16.18)

the two systems against a 0.03 s difference in the Dubois and Charpillat (2017) study. This improvement may be explained by the hardware evolution of the Kinect sensor. In particular, the Kinect v2 is known to be more accurate than the v1 for depth measurements (Gonzalez-Jorge et al., 2015; Wasenmüller and Stricker, 2016).

If we now focus more specifically on gait parameters, the agreement levels obtained in our study for gait speed (0.94–0.96) are in line with those reported in the literature, namely 0.90–0.99 depending on the method used (ICC, Pearson or CCC) (Clark et al., 2013; Geerse et al., 2015; Mentiplay et al., 2015). Similarly, for step length, values ranging from 0.92 to 0.97 correspond well to the 0.80 to 0.99 range usually reported (Clark et al., 2013; Geerse et al., 2015; Mentiplay et al., 2015; Motiian et al., 2015). Regarding step time, we observed values ranging from 0.93 to 0.94, which lies in the upper end of the “usual” range because the agreement values usually reported are in the 0.77 to 0.92 range (Clark et al., 2013; Geerse et al., 2015; Mentiplay et al., 2015; Xu et al., 2015; Motiian et al., 2015). If we look at the limits of agreement, the values we found for step length (−2.10 to 6.01) and gait speed (−6.134 to 14.145) were relatively high. However, Motiian et al. (2015) observed still higher limits both for step length (−8.167 to 5.079 for left step and −10.656 to 6.441 for right step) and gait speed (−15.966 to 13.413). In contrast, Geerse et al. (2015) observed more narrow limits of agreement, namely values ranging from −1.4 to 1.2 for step length and from 0.1 to 2.1 for gait speed. It is important to note that in most studies, the limits of agreement are given as the average of all sequences for any given participant (one value per participant). Accordingly, one can expect relatively narrow limits of agreement. When applying the same method and averaging all sequences by participant, we also obtained more narrow limits of agreement, namely a bias of 1.96, −0.003, −0.000, 4.01 with limits of 0.84 to 3.08, −0.016 to 0.010, −0.038 to 0.037, 0.18 to 7.83 for step length, step duration, cadence and gait speed, respectively. Although the limits of agreement we measured are fairly larger than those reported in the literature, the reverse tendency was observed for PE. Indeed, the PE was smaller in our study (6.28% for step length, 7.17% for step duration, 7.05% for cadence and 8.96% for gait speed). For example, in Motiian et al. (2015), PE was 21% for step length, 12.8% for gait speed and 15% for step duration. In Clark et al. (2013), the PE were similar to ours for gait speed (8%) and step length (5%) but larger for step duration (19%). Overall, and in view of these results, we are confident that our Kinect-based method can be used to reliably extract gait parameters.

In the geriatric literature, step length, step duration, cadence and gait speed are acknowledged as highly relevant to assess fall risks. Here, we showed that these four parameters can successfully be extracted with our Kinect-based system to discriminate young people from older individuals, who are at higher risk of fall (World Health Organization, 2008; Gryfe et al., 1977; Lord et al., 2001). Importantly, our system also allowed us to discriminate two groups of elderly people, namely individuals aged 67–73 vs 76–89. The two parameters underlying this latter discrimination were step length and gait speed, which are therefore the most auspicious parameters for assessing fall risk using our system. Future studies will focus on identified fallers having distinct clinically-determined risks of fall.

Using a simple representation of the walking individual, namely the geometric center, we were able to extract the most relevant gait parameters as accurately as with a more “complex” skeleton-based method. We also showed that these parameters can be accurately extracted over a wide range of age categories. We believe that in addition to being easier to use, non skeletal-based approaches such as ours are also less susceptible to visual occlusions and therefore more robust than commercially available

skeleton-based methods (marker-based motion capture and Microsoft Kinect SDK). In that respect, our approach is more flexible, in that it can be used in a larger range of situations. Therefore, this system would be an excellent automatic alternative or complement to the clinical tests currently performed by healthcare professionals to assess fall risk in the elderly.

Conflicts of interest

The authors in this study declare that there is no conflict of interest.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.jbiomech.2018.01.024>.

References

- Auvinet, B., Berrut, G., Touzard, C., Collet, N., Chaleil, D., Barrey, E., 2003. Gait abnormalities in elderly fallers. *J. Aging Phys. Activ.*, 40–52.
- Baldewijns, G., Verheyden, G., Vanrumste, B., Croonenborghs, T., 2014. Validation of the Kinect for gait analysis using the GAITRite walkway. In: 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 5920–5923.
- Carrasco, J.L., Phillips, B.R., Puig-Martinez, J., King, T.S., Chinchilli, V.M., 2013. Estimation of the concordance correlation coefficient for repeated measures using SAS and R. *Comput. Methods Programs Biomed.* 109, 293–304.
- Carstensen, B., Simpson, J., Gurrin, L.C., 2008. Statistical models for assessing agreement in method comparison studies with replicate measurements. *Int. J. Biostat.* 4, 1.
- Chang, C.-Y., Lange, B., Zhang, M., Koenig, S., Requejo, P., Somboon, N., Sawchuk, A. A., Rizzo, A.A., 2012. Towards pervasive physical rehabilitation using Microsoft Kinect. In: 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops. IEEE, pp. 159–162.
- Clark, R.A., Bower, K.J., Mentiplay, B.F., Paterson, K., Pua, Y.-H., 2013. Concurrent validity of the Microsoft Kinect for assessment of spatiotemporal gait variables. *J. Biomech.* 46, 2722–2725.
- Critchley, L.A.H., Critchley, J.A.J.H., 1999. A meta-analysis of studies using bias and precision statistics to compare cardiac output measurement techniques. *J. Clin. Monit. Comput.* 15, 85–91.
- Dubois, A., Charpillat, F., 2017. Measuring frailty and detecting falls for elderly home care using depth camera. *J. Ambient Intell. Smart Environ.* 9 (4), 469–481.
- Gabel, M., Gilad-Bachrach, R., Renshaw, E., Schuster, A., 2012. Full body gait analysis with Kinect. In: Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 1964–1967.
- Galna, B., Barry, G., Jackson, D., Mhiripiri, D., Olivier, P., Rochester, L., 2014. Accuracy of the Microsoft Kinect sensor for measuring movement in people with Parkinson's disease. *Gait Posture* 39 (4), 1062–1068.
- Geerse, D.J., Coolen, B.H., Roerdink, M., 2015. Kinematic validation of a multi-Kinect v2 instrumented 10-meter walkway for quantitative gait assessments. *PLoS One* 10, e0139913.
- Gonzalez-Jorge, H., Rodríguez-González, P., Martínez-Sánchez, J., González-Aguilera, D., Arias, P., Gesto, M., Díaz-Vilariño, L., 2015. Metrological comparison between Kinect i and Kinect ii sensors. *Measurement* 70, 21–26.
- Gryfe, C.I., Amies, A., Ashley, M.J., 1977. A longitudinal study of falls in an elderly population: I. Incidence and morbidity. *Age Ageing* 6 (4), 201–210.
- Hausdorff, J.M., Rios, D.A., Edelberg, H.K., 2001. Gait variability and fall risk in community-living older adults: A 1-year prospective study. *Arch. Phys. Med. Rehab.* 82 (8), 1050–1056.
- Lord, S.R., Sherrington, C., Menz, H.B., 2001. *Falls in Older People: Risk Factors and Strategies for Prevention*. Cambridge University Press.
- Mentiplay, B.F., Perraton, L.G., Bower, K.J., Pua, Y.-H., McGaw, R., Heywood, S., Clark, R.A., 2015. Gait assessment using the Microsoft Xbox one Kinect: concurrent validity and inter-day reliability of spatiotemporal and kinematic variables. *J. Biomech.* 48, 2166–2170.
- Motiian, S., Pergami, P., Guffey, K., Mancinelli, C.A., Doretto, G., 2015. Automated extraction and validation of children's gait parameters with the Kinect. *Biomed. Eng. Online* 14, 112.
- Shrout, P.E., Fleiss, J.L., 1979. Intraclass correlations: uses in assessing rater reliability. *Psychol. Bull.* 86 (2), 420–428.
- Springer, S., Yogev Seligmann, G., 2016. Validity of the Kinect for gait assessment: a focused review. *Sensors* 16, 194.
- Stone, E.E., Skubic, M., 2011. Evaluation of an inexpensive depth camera for passive in-home fall risk assessment. In: 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops. IEEE, pp. 71–77.

- Studenski, S., Perera, S., Wallace, D., Chandler, J.M., Duncan, P.W., Rooney, E., Fox, M., Guralnik, J.M., 2003. Physical performance measures in the clinical setting. *J. Am. Geriatr. Soc.* 51 (3), 314–322.
- Wasenmüller, O., Stricker, D., 2016. Comparison of kinect v1 and v2 depth images in terms of accuracy and precision. In: *Asian Conference on Computer Vision*. Springer, pp. 34–45.
- World Health Organization. Ageing and Life Course Unit, 2008. *Global Report on Falls Prevention in Older Age*. World Health Organization.
- Xu, X., McGorry, R.W., Chou, L.-S., Lin, J.-h., Chang, C.-C., 2015. Accuracy of the microsoft kinect™ for measuring gait parameters during treadmill walking. *Gait Posture* 42 (2), 145–151.
- Ye, M., Yang, C., Stankovic, V., Stankovic, L., Kerr, A., 2016. A depth camera motion analysis framework for tele-rehabilitation: motion capture and person-centric kinematics analysis. *IEEE J Sel Top Sign Process* 10 (5), 877–887.