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Accuracy and reliability of the RGB-D camera for measuring walking speed on a treadmill

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ABSTRACT

Aim: RGB-D cameras (Red Green Blue + Depth) are widely employed in exergames designed to physically stimulate elderly people. Nevertheless, the intensity of the physical activity reached with the existing solutions is rarely sufficient to obtain a real impact on the physical fitness and thus on the health status of this population. In this context, a Point Cloud Based System (PCBS) has been developed to interface ordinary motorized treadmills with exergames through a simple RGB-D camera, to induce players to perform physical activities at higher intensities. The goal of this study was to assess the accuracy and reliability of PCBS to measure the walking speed of a subject on a standard motorized treadmill based on the image streams of an RGB-D camera.

Methods: 36 participants performed three 10 min walking exercises, divided in 5 blocks of 2 min at the following constant ordered speeds: 0.42, 0.69, 0.97, 1.25 and 1.53 m s^{-1}. The measured walking speeds are compared to those obtained through a Marker Based Control System (MBCS).

Results: Results showed a high system accuracy (bias: 0.013 $\pm$ 0.015 m s^{-1}), a good reliability (ICC = 0.63–0.91) and a low variability (SEM = 1–5%; MD = 2.7–14%).

Discussion: Accuracy and reliability of PCBS are consistent with those obtained in similar existing systems measuring gait parameters.

Conclusion: Within the context of the development of exergames, PCBS may be combined with exergames to perform physical activities at sufficiently high intensities in the elderly population, in order to improve their physical health and possibly prevent/delay cognitive impairment.

1. Introduction

There is major interest nowadays in Moderate-High Intensity Aerobic Activities (MHIAA) for non-pharmacological interventions in elderly suffering from neurodegenerative diseases like Alzheimer's Disease and Related Disorders (ADRD) [1,2]. More and more evidence is available on the positive effects of MHIAA on neuroplasticity, cardiorespiratory fitness and ADRD, in particular concerning locomotion exercises such as walking, biking or rowing [3–5]. Nevertheless, the monotony of the practice of these activities is an important drawback, which has lead to the development of video games for physical exercises (or exergames) to make it more attractive [6,7]. The most common and affordable exergames allow the player to interact with the game using motion sensors based on RGB-D cameras (Red Green Blue + Depth) for the Microsoft® Kinect™.

Video games using Kinect™ sensors are already employed to stimulate physical activities in elderly people [8,9]. However, these recent studies have demonstrated that commercial games based on this technology stimulate only slightly the cardiorespiratory system limiting therefore the possible benefits on physical fitness and cognitive function [9]. This small physiological stimulus is

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mainly related to the depth limitation of the sensors (up to 5 m to minimize errors) [10]. In fact, this limitation implies to stay on the spot in a small area in front of the RGB-D camera and mainly exercising upper limbs. Therefore, the use of a treadmill is a good trade-off to perform MHIAA within the field of view of the RGB-D camera.

Concerning the Kinect™, Microsoft® provides a library which computes a skeletal representation of the human body. This skeletal representation has been studied as a tool for evaluating static foot posture [11], postural control assessment [12], movement detection [13], over-ground walking [14] and treadmill walking without occlusion (without grabbing frame) [15,16]. However, the measurement of the walking speed on a standard treadmill through this Microsoft® library has not been investigated so far because skeletal representation becomes very noisy with the partial occlusion of the treadmill frame. In this case, it becomes impossible to measure a coherent walking speed.

Several ADRD patients suffer from walking disorders such as gait apraxia [17]. Gait parameters seem similar during overground walking and treadmill walking [18]. Hence, it would be interesting to combine treadmill MHIAA with gait analysis during walking. Within the exergames context, in order to keep the system affordable (i.e. treadmills that can be directly interfaced with exergames are generally expensive) and secure (with a grabbing frame), a Point Cloud Based System (PCBS) has been developed using only the images streams (depth and color images) provided by the RGB-D camera. PCBS is adjustable to any kind of treadmill, and measures the walking speed of a person using feet detection. The final purpose of this system is to be combined with an exergame intended for people suffering from ADRD, where the avatar will move forward according to the walking speed of the person. Therefore, this exergame could allow combining MHIAA with the analysing of walking disorders.

An exergame is a type of Information and Communication Technology (ICT) which allows humans to interact with virtual environments. This type of interaction can be facilitated by the presence of some ergonomic criteria. For instance, Bastien and Scapin [19,20] described ergonomic criteria which facilitate adhesion and interactions between humans and virtual environments. Some of these criteria highlight the importance of using coherent and consistent controllers in which errors and ambiguities are limited. Within this context, PCBS measures should be sufficiently accurate and reliable to be integrated as controller within an exergame.

Therefore, the goal of this study was to assess the accuracy and reliability of PCBS to measure the walking speed of a person on a standard motorized treadmill.

2. Methods

2.1. Subjects

Thirty six healthy individuals (17 males, 19 females, age: 32.1 ± 7.6 years, height: 171.1 ± 9.1 cm, weight: 67.4 ± 13.6 kg) without any physical or cognitive disorder that could influence the gait were recruited to participate in this study. The experimental design was approved by the local hospital Ethics Committee, and the protocol was performed in line with the Declaration of Helsinki. After comprehensive verbal and written explanations of the study and its aims, all subjects gave their written informed consent for participation.

2.2. Materials

During this experiment, walking participants were recorded using an Asus® Xtion PRO LIVE RGB-D camera which provides real 3D information of the scene. This camera and the Kinect sensor are based on the same PrimeSense infra-red technology. It was placed in front of the motorized treadmill (Kettler® Track Motion, speed steps: $0.028\ \mathrm{m\,s^{-1}}$, walking surface: $48\ \mathrm{cm} \times 132\ \mathrm{cm}$), at a distance of 2 meters. All processes and records were performed under Fedora 19, processor Intel Xeon 2.4 GHz, 16GB memory.

2.3. Procedure

Participants were required to wear comfortable clothes to walk on the treadmill (flat sport shoes or flat street shoes, shorts, trousers or jeans). Each participant was asked to perform three 10-min walking exercises. Between trials, a 5-min break was proposed to the participant, to allow him/her to rest and not to influence the subsequent exercise. Each 10-min exercise consisted of the following five 2-min sub-exercises in the following ordered speeds covering the full walking spectrum: 0.42, 0.69, 0.97, 1.25 and $1.53\ \mathrm{m\,s^{-1}}$ (i.e., 1.5, 2.5, 3.5, 4.5 and $5.5\ \mathrm{km\,h^{-1}}$). Running is generally preferred at a speed higher than $1.53\ \mathrm{m\,s^{-1}}$ [21]. Participants were simply asked to follow the speed of the treadmill. Each trial (10-min exercise) began when the investigator switched on the RGB-D camera and opened the application for capturing the scene without subject (see Section 2.5.2). Next, subject entered the scene and stepped onto the motorized treadmill. Then, he/she started the treadmill and fixed the speed at $0.42\ \mathrm{m\,s^{-1}}$. Every 2 min, the participant increased by himself the treadmill speed by $0.028\ \mathrm{m\,s^{-1}}$ until $1.53\ \mathrm{m\,s^{-1}}$. At the end of each trial, participant stopped the treadmill and leaved the scene and the investigator closed the application and shut down the RGB-D camera.

2.4. Marker Based Control System (MBCS)

MBCS consists in a white mark painted on the dark walking surface of the treadmill and detected using local image intensity in order to measure the real rotating speed (see Fig. 1).

2.5. Point Cloud Based System (PCBS)

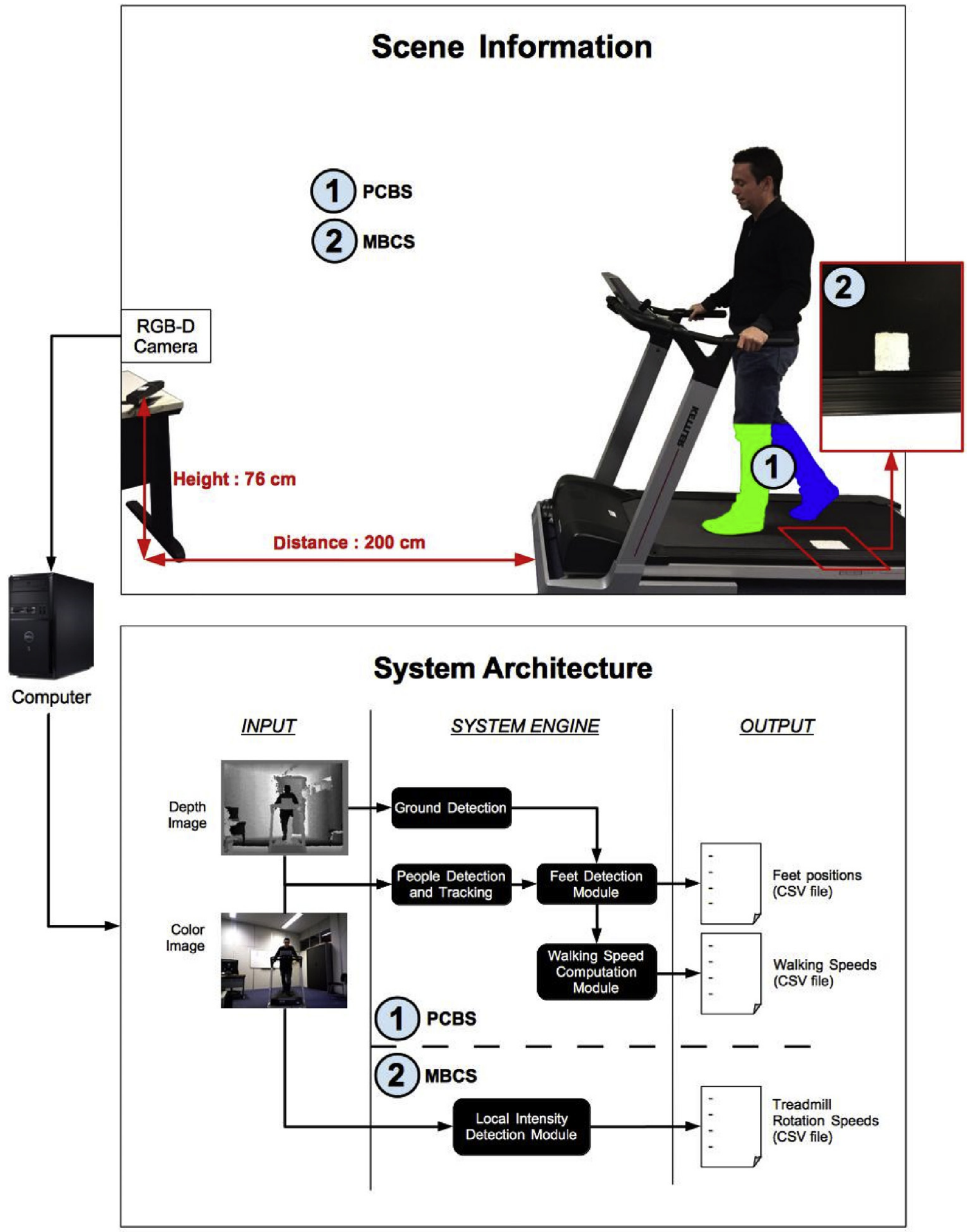
In the computer vision domain, the computation of the walking speed of a person can be estimated from the displacement of the center of gravity of the person. Here, employing a treadmill forced us to develop a different method to measure that speed. The proposed system is presented in four main subsections. The first three subsections present how the feet of the person are detected from the cloud of points and the ground detection, and how the noise is filtered from this detection. The computation of the speed based on the successive positions of the feet is described in the last subsection. For more information on the system architecture, see Fig. 1.

2.5.1. People detection and tracking

The first step is to detect and track the person on the scene. People detection is performed at each frame using a background subtraction algorithm proposed by Nghiem et al. [22]. A multi-feature algorithm, such as 2D size, 3D displacement, color histogram and dominant color, proposed by Chau et al. [23] is used for tracking.

2.5.2. Ground detection

In particular cases (e.g., when depth information is missing), some points belonging to the ground can be wrongly included in the cloud of point of the person. In that case, the ground plane should be estimated to correct the classification of the points. Based on the lowest part of the scene (with the assumption that the ground pixels cover at least 10% of the image), the plane equation is computed as the plane that minimize its distance to the ground points. Once this plane equation has been estimated, the cloud of



RGB-D = Red Green Blue + Depth

PCBS = Point Cloud Based System

MBCS = Marker Based Control System

Fig. 1. Scene information and systems architecture. MBCS: this system computes the rotating speed of the treadmill and therefore the real walking speed of the person. Based on the color intensity of a zone manually set of the RGB image (located on the treadmill, where the white mark pass by), this system detects each round of the treadmill, and knowing the length of the treadmill, the speed is computed thanks to the time elapsed between each round.

point of the person is filtered and the points belonging to the ground removed (Fig. 2A and B).

2.5.3. Feet detection

After this filtering process, only the lowest body part of the person is kept (25% of the lowest points). Each remaining point is then classified as belonging to the right or left leg, depending on their distance with the right and left extrema of the cloud (Fig. 2C, blue and green legs). Both legs are then splitted vertically in halves of the same height and the straight line passing through the center of gravity of each part (Fig. 2C, orange dots and straight line) represents the skeleton of the legs. Finally, feet are the projections of the lowest points of the legs on these straight lines (Fig. 2C, yellow dots).

2.5.4. Speed computation

During walking, the gait parameters are easier to analyze since the end of each step is determined by the moment where each foot is on the ground with a maximum distance between the feet [24]. After a quick observation of the successive positions of the feet on the frames, and more particularly of the distance between these feet, it appears that the different

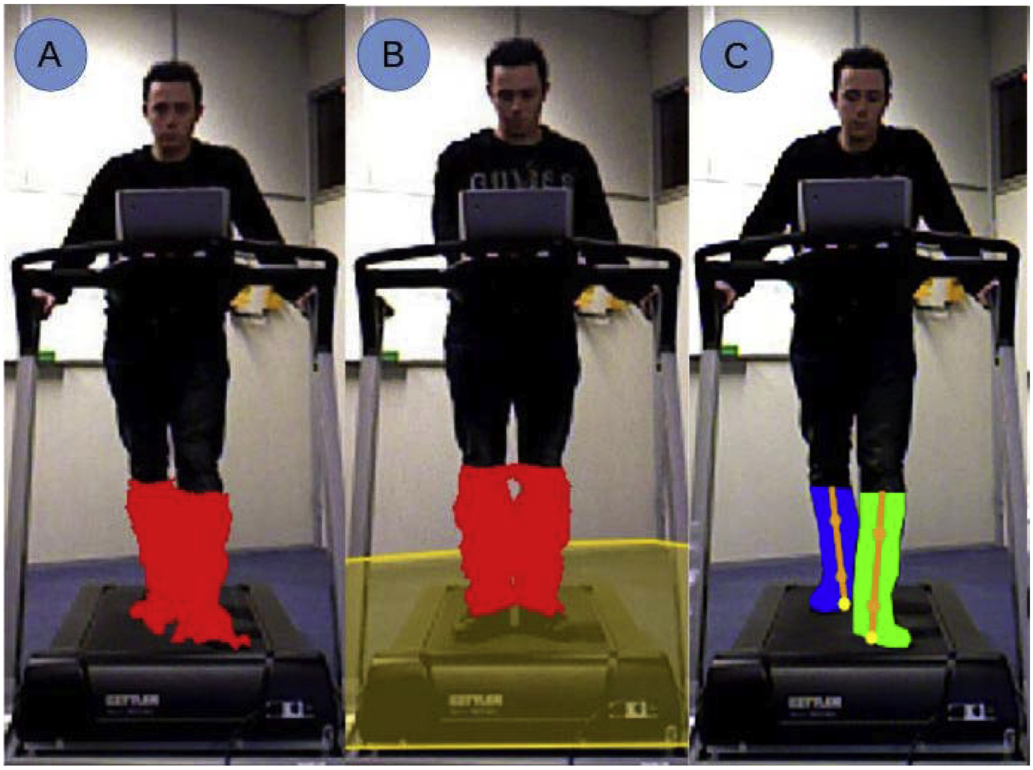


Fig. 2. Point cloud filtering. (A) Without filter, some ground points are included in the cloud of the person. (B) A filter is applied depending on the distance between the person's points and the plane of the treadmill (removed if less than 2 cm). (C) Legs points classification (left and right, respectively green and blue) with legs skeleton line passing by the center of gravity of halves legs points (orange line and dots) and feet detection (yellow points). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

walking phases can be extracted from this distance (Fig. 3, left). For instance, local minima (Fig. 3, left, green crosses) correspond to the time when the back foot is brought back to the front, exactly when it passes close to the other foot (moment in the walking cycle where the distance between feet is minimum). On the contrary, local maxima (Fig. 3, left, red crosses) are the exact time when the distance between feet is maximum, that is to say when the back foot is again put on the ground in front. The instantaneous speed of the person is then measured from the distance at this precise moment and the elapsed time since last maximum. Basic filtering and smoothing methods are also used like averaging the speed over the five last steps of removing steps shorter than 12 cm.

2.6. Data and statistical analysis

All statistical analyses were performed with STATISTICA 7.0 software and Excel (Microsoft, USA) for Windows.

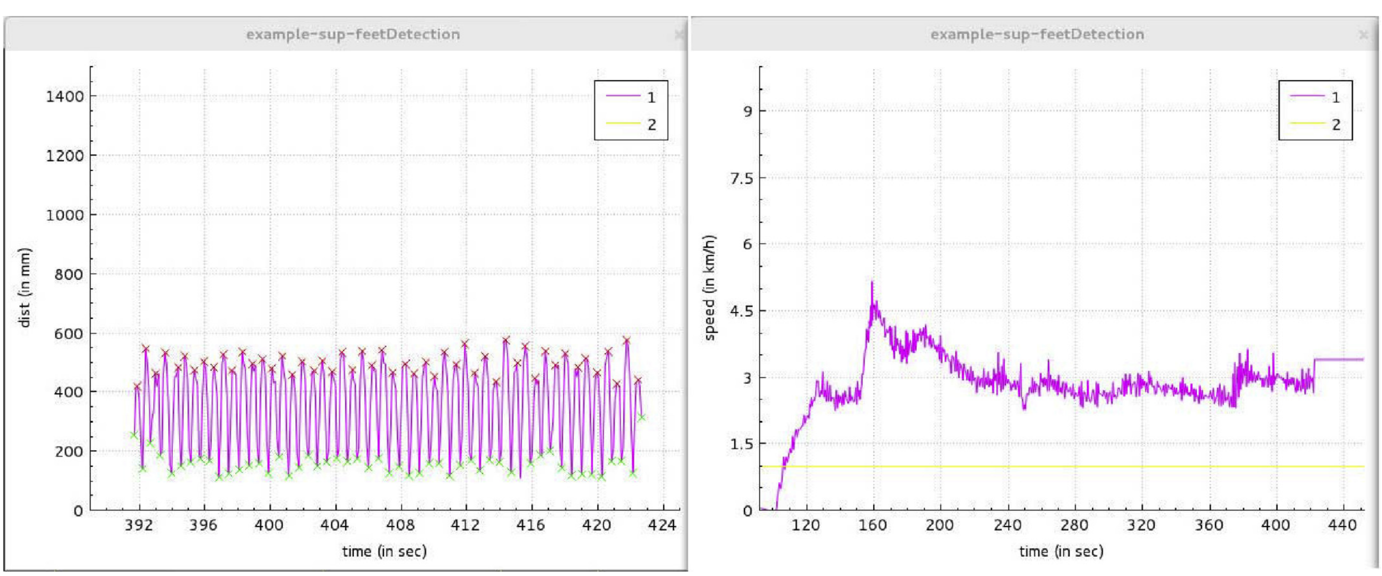


Fig. 3. Left: graph of the distance between the feet in function of the time (red and green crosses represent respectively local maxima and minima). Right: graph of the speed in function of the time. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

Accuracy was assessed by the comparison of speed measures between PCBS and MBCS. Data were analyzed using two way repeated measures ANOVA: Systems (PCBS vs. MBCS) and Speed (0.42 vs. 0.69 vs. 0.97 vs. 1.25 vs. 1.53 m s^{-1}). When a significant effect was found, post hoc tests were performed using Newman–Keuls procedures. Differences were significant for $p < .05$.

Speed measures relative reliability of PCBS and MBCS (3 trials for each of the five speeds) were evaluated using intra-class correlation coefficient (ICC 2, 1 [25,26]). The following general guidelines of Munro were used [27]: 0–0.25 little correlation, 0.26–0.49 low, 0.50–0.69 moderate, 0.70–0.89 high and 0.9–1.0 very high. Speed measures absolute reliability for both methods were evaluated using the Standard Error of Measurement (SEM) or typical error. SEM was expressed as a coefficient of variation and was determined accordingly to the recommendations of Hopkins [28] and Weir [26]. Smaller values of SEM reflect more reliable measures. The SEM was expressed as a percentage of the grand mean (SEM% = SEM/mean × 100). This form of the typical error allows for comparison of absolute reliability between measurements and groups. SEM was also used to determine the Minimum Difference (MD) to be considered "real", calculated as suggested by Bedard et al. [29]: MD = SEM × 1.96 × $\sqrt{2}$. ICC, SEM and MD were used for the more robustness compared with Pearson R, the Coefficient of Variation (CV) and the Limit Of Agreements (LOA or Bland–Altman plots) for reliability analysis [25,26].

3. Results

3.1. Walking speed accuracy

All subjects completed the protocol. ANOVA revealed a main effect of speed ($F_{(4,140)} = 63{,}007$, $p < .05$) and a main effect of system ($F_{(1,35)} = 5.0420$, $p < .05$). Whatever the system measured at 0.42, 0.69, 0.97, 1.25 and 1.53 m s^{-1} were statistically different among each other. Furthermore, measured speeds with PCBS were greater than with MBCS (mean difference or bias: 0.013 ± 0.015 m s^{-1}). Moreover, a significant interaction effect was observed ($F_{(4,140)} = 19.141$, $p < .05$). Post hoc analysis reveals that measured speeds with PCBS were significantly greater than MBCS at the lowest speeds (0.42, 0.69 and 0.97 m s^{-1}) but significantly lower at 1.53 m s^{-1} (Table 1).

3.2. Walking speed reliability

The inter-trial reliability measures for each system are provided in Table 2. Concerning PCBS measured speeds, we found moderate to high relative reliability (ICC ranged from 0.63 to 0.91). Concerning MBCS measured speeds, we found low to high relative reliability (0.15–0.91). Overall, ICC values were higher for PCBS than for MBCS. Furthermore, both systems show a low variability, slightly larger for PCBS than for MBCS (respectively, SEM ranged from 1% to 5% and 0% to 0.2%, and MD ranged from 2.7% to 14% and 0.1% to 0.9%).

4. Discussion

4.1. Accuracy

In this study we have observed a statistically significant difference between our two systems with a recorded bias of 0.013 ± 0.015 m s^{-1} (see Table 1) and an interaction effect between walking speed and system was found. Specifically, the higher is the speed, the smaller is the gap between two measured values. To the best of our knowledge, no study on standard treadmill compared so far walking speed accuracy between RGB-D camera and control system. In the present study, the difference between PCBS and MBCS was similar to the treadmill console compared to MBCS (bias between PCBS and MBCS: 0.013 ± 0.015 m s^{-1}; bias between treadmill console and MBCS: 0.012 ± 0.013, see Table 1), demonstrating a however a good level of accuracy. The bias between the treadmill console and MBCS can be explained by heel strikes slowing down the treadmill rotation speed [30].

The remaining inaccuracies in the speed computation were mainly due to the quality of the depth stream and of the detected feet positions, which can be compared in future studies using a golden-standard movement analysis system such as Vicon. These results are consistent with other studies which showed a high level of accuracy using Kinect™ compared to control system for foot static posture [11] and postural control [12]. Clark et al. [14] showed a similar mean difference for measured speed during over-ground walking between Kinect™ library and Vicon (bias: 0.01 m s^{-1}). In similar conditions, Xu et al. [16] showed a very high accuracy in the computation of the walking time phases on a frameless treadmill when comparing Kinect™ library and

Table 1
Accuracy of measured speeds with PCBS and MBCS.

Speeds (m s^{-1})		PCBS Mean (SD)		MBCS Mean (SD)		Bias (m s^{-1})
		Each trial	Mean of 3 trials	Each trial	Mean of 3 trials	
0.42 m s^{-1}	Trial 1	0.43 (0.03)	0.44 (0.04)	0.42 (0.00)	0.42 (0.00)	0.02
	Trial 2	0.44 (0.04)		0.42 (0.00)		
	Trial 3	0.45 (0.04)		0.42 (0.00)		
0.69 m s^{-1}	Trial 1	0.71 (0.04)	0.71 (0.04)	0.69 (0.00)	0.69 (0.00)	0.02
	Trial 2	0.71 (0.04)		0.69 (0.00)		
	Trial 3	0.71 (0.04)		0.69 (0.00)		
0.97 m s^{-1}	Trial 1	0.98 (0.04)	0.98 (0.04)	0.96 (0.00)	0.96 (0.00)	0.02
	Trial 2	0.98 (0.04)		0.96 (0.00)		
	Trial 3	0.98 (0.04)		0.96 (0.00)		
1.25 m s^{-1}	Trial 1	1.24 (0.05)	1.24 (0.04)	1.23 (0.00)	1.23 (0.00)	0.01
	Trial 2	1.24 (0.04)		1.23 (0.00)		
	Trial 3	1.24 (0.04)		1.23 (0.00)		
1.53 m s^{-1}	Trial 1	1.49 (0.05)	1.49 (0.05)	1.50 (0.00)	1.50 (0.00)	−0.01
	Trial 2	1.49 (0.05)		1.50 (0.00)		
	Trial 3	1.49 (0.05)		1.50 (0.00)		

0.42 m s^{-1} = 1.5 km h^{-1}; 0.69 m s^{-1} = 2.5 km h^{-1}; 0.97 m s^{-1} = 3.5 km h^{-1}; 1.25 m s^{-1} = 4.5 km h^{-1} and 1.53 m s^{-1} = 5.5 km h^{-1}.
PCBS: Point Cloud Based System; MBCS: Marker Based Control System; Bias: mean difference.

Table 2
Reliability of measured speeds with PCBS and MBCS.

Speeds ($m\,s^{-1}$)		PCBS		MBCS	
		Trials 1–2	Trials 2–3	Trials 1–2	Trials 2–3
$0.42\,m\,s^{-1}$	Mean	0.44	0.45	0.42	0.42
	ICC	0.63	0.84	0.91	0.29
	SEM value (%)	0.022 (5.0)	0.015 (3.4)	0.000 (0.1)	0.001 (0.3)
	MD value (%)	0.061 (14.0)	0.042 (9.4)	0.001 (0.2)	0.004 (0.9)
$0.69\,m\,s^{-1}$	Mean	0.71	0.71	0.69	0.69
	ICC	0.80	0.88	0.74	0.63
	SEM value (%)	0.018 (2.5)	0.014 (2.0)	0.000 (0.1)	0.000 (0.1)
	MD value (%)	0.049 (6.9)	0.039 (5.5)	0.001 (0.2)	0.001 (0.2)
$0.97\,m\,s^{-1}$	Mean	0.98	0.98	0.96	0.96
	ICC	0.74	0.90	0.62	0.76
	SEM value (%)	0.021 (2.2)	0.013 (1.3)	0.001 (0.1)	0.000 (0.0)
	MD value (%)	0.059 (6.0)	0.036 (3.6)	0.001 (0.2)	0.001 (0.1)
$1.25\,m\,s^{-1}$	Mean	1.24	1.24	1.23	1.23
	ICC	0.81	0.88	0.65	0.71
	SEM value (%)	0.020 (1.6)	0.015 (1.2)	0.001 (0.0)	0.001 (0.0)
	MD value (%)	0.055 (4.4)	0.042 (3.4)	0.002 (0.1)	0.001 (0.1)
$1.53\,m\,s^{-1}$	Mean	1.49	1.49	1.5	1.5
	ICC	0.82	0.91	0.13	0.66
	SEM value (%)	0.021 (1.4)	0.015 (1.0)	0.003 (0.2)	0.001 (0.1)
	MD value (%)	0.057 (3.8)	0.041 (2.7)	0.009 (0.6)	0.002 (0.2)

$0.42\,m\,s^{-1} = 1.5\,km\,h^{-1}$; $0.69\,m\,s^{-1} = 2.5\,km\,h^{-1}$; $0.97\,m\,s^{-1} = 3.5\,km\,h^{-1}$; $1.25\,m\,s^{-1} = 4.5\,km\,h^{-1}$ and $1.53\,m\,s^{-1} = 5.5\,km\,h^{-1}$.
ICC: Intraclass Correlation Coefficient; SEM: Standard Error of Measurement; MD: Minimum Difference to be considered "real"; PCBS: Point Cloud Based System; MBCS: Marker Based Control System; Bias: mean difference.

optotrack. In the context of exergames, this level of accuracy seems therefore to be sufficient to use PCBS as controller. In interactions between humans and virtual environments, explicit control, as described by Bastien and Scapin [19,20], is a key aspect. This suggests that the users should always be in control of the system processing. Errors and ambiguities are limited when inputs are under their control. PCBS accuracy should be sufficient to detect no walking condition and many levels of walking speed. Combined with an exergame, PCBS can allow the user to control the speed of displacement or immobility of the avatar within the game (e.g., avatar changing displacement speed by 0.28 $m\,s^{-1}$ steps). In this case, the risk of generating ambiguities is minimal.

4.2. Reliability

ICCs for the two systems were moderate to high. For the PCBS, this value was around 0.8 when is it 0.6 for MBCS. Moreover, our measures showed low variability (Table 2). These results are consistent with other studies using RGB-D cameras which showed moderate to high ICC values in assessment of static foot posture [11], postural control [12] and body movements [13]. However, studies on over-ground walking [14] and treadmill walking [15,16] did not test RGB-D cameras reliability. In the present study, the smaller ICC for MBCS can be explained by the heel strike on the treadmill, which can modify the measured rotation speed of the treadmill between trials. However, the slightly larger variability for PCBS was mainly due to the variation of the signal to detect. In fact, MBCS is easier and more robust to detect since it is consistent and uniform in shape that appears on a regular time intervals, while for the PCBS, it depends on parameters varying from one person to another (e.g., morphology, clothes, gait), and therefore influencing the measured speed. For instance, the pre-tests of the system showed that if the person was wearing long skirt or wide pants, the results were badly influenced. In the context of this experiment, the choice has been made not to standardize clothes and morphologies to check whether or not our system was usable in more ecological conditions. In the context of exergames, this level of reliability seems to be sufficient to use PCBS as controller.

5. Conclusion

This paper tested PCBS accuracy and reliability. The results showed that the speed measured by the PCBS is enough accurate and reliable for treadmill walking at a constant speed. Thus, within the context of the development of exergames and according to the explicit control ergonomic criteria described by Bastien and Scapin [19,20], PCBS can be used as a game controller. The player will be able to control avatar walking speed with a minimal risk of generating errors and ambiguities, which will also guarantee game adhesion and security. Another benefit of PCBS is its extensibility and its affordability. In fact, while the use of other systems such as a treadmill that can be interfaced directly with the game can be limited to walking information (e.g., speed, distance), the view of the camera provides also contextual information on the scene. PCBS can therefore be extended, for instance, to a deeper assessment of the gait (e.g., symmetry, step length, cadence) or to the detection of upper limb movements. Theses parameters are important in the context of ADRD associated with gait apraxia [17]. Hence, PCBS could combine treadmill MHIAA, gait analysis and gait rehabilitation. Studies on PCBS accuracy at variable speed and on PCBS relevance in assessing gait apraxia will be necessary to confirm the potential of PCBS and this operational usability.

Conflicts of interest

No conflicts of interest to report.

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