Validation of a Method for Real Time Foot Position and Orientation Tracking With Microsoft Kinect Technology for Use in Virtual Reality and Treadmill Based Gait Training Programs

Gabriele Paolini, Agnese Peruzzi, Anat Mirelman, Andrea Cereatti, Stephen Gaukrodger, Jeffrey M. Hausdorff, and Ugo Della Croce

***Abstract*—The use of virtual reality for the provision of motor-cognitive gait training has been shown to be effective for a variety of patient populations. The interaction between the user and the virtual environment is achieved by tracking the motion of the body parts and replicating it in the virtual environment in real time. In this paper, we present the validation of a novel method for tracking foot position and orientation in real time, based on the Microsoft Kinect technology, to be used for gait training combined with virtual reality. The validation of the motion tracking method was performed by comparing the tracking performance of the new system against a stereo-photogrammetric system used as gold standard. Foot position errors were in the order of a few millimeters (average $RMSD$ from 4.9 to 12.1 mm in the medio–lateral and vertical directions, from 19.4 to 26.5 mm in the anterior-posterior direction); the foot orientation errors were also small (average $\%RMSD$ from 5.6% to 8.8% in the medio–lateral and vertical directions, from 15.5% to 18.6% in the anterior–posterior direction). The results suggest that the proposed method can be effectively used to track feet motion in virtual reality and treadmill-based gait training programs.**

***Index Terms*—Foot tracking, gait, kinect, training program, virtual reality.**

I. Introduction

VIRTUAL reality (VR) has been used for rehabilitation of different patient populations in an effort to enhance human movement performance. Advantages of VR include the ability to control the intensity of the treatment, while providing feedback to enhance motivation and performance [1]–[4]. The user's movement is usually tracked and reproduced in the virtual environment in real-time to achieve interactivity. Different techniques have been used to track human movement. Stereo-photogrammetric systems (SP) are very accurate, but their use is limited by their cost, time, space, and expertise requirements. Magnetic based motion capture systems suffer from interference of undesired magnetic fields in the measurement volume [5], [6]. Wearable inertial sensors are a valuable alternative, however the drift affecting their output signals limits the reliability of the estimation of the derived position and orientation [7]–[9].

Recently, low cost depth sensing cameras have become commercially available. One example is the Microsoft Kinect. The Kinect is a motion sensing device that combines a color RGB video camera with an infrared-based depth sensor composed of an infrared (IR) emitter producing structured IR light, and a single IR sensitive camera. The distance between the sensor and the environment is estimated by evaluating the modified pattern of structured light deviated by the objects in the field of view with respect to the same pattern, identified during the factory calibration of the depth sensing element. The Kinect ships with an integrated full body skeleton tracker, and open access software libraries are provided in order to extract information from the device.

The accuracy of the measurements given by the Kinect sensor has been recently evaluated in several different applications. Khoshelham and Elberink showed that the accuracy of the Kinect depth measurements changes with the distance of the sensor from the objects in the environment. They reported that the error of depth measurement increases quadratically with the distance from the sensor, ranging from a few millimeters up to about 40 mm at maximum distance from the sensor (4 m) [10].

In a validation study focused on upper limb motor tasks, the trajectories estimated by the Kinect were compared with those estimated by a SP system [11]. The results showed that the quality of the Kinect tracking was acceptable for the specific application. Clark *et al.* [12] validated the accuracy of the joint center positions provided by the Kinect using the corresponding trajectories estimated using a full body model and a SP system during three postural control assessment tasks as a gold standard.

The above-mentioned studies used the Kinect's built-in software tool for full human body tracking. However, this tool does not allow the tracking of the motion of one or more isolated body

Manuscript received April 16, 2013; revised August 09, 2013; accepted August 21, 2013. Date of publication October 09, 2013; date of current version September 04, 2014. The research leading to these results has received funding from the European Union-Seventh Framework Programme (FP7-HEALTH-2011) under grant agreement n. 278169 (V-TIME).

G. Paolini, A. Peruzzi, A. Cereatti, and U. Della Croce are with the Information Engineering Unit of the POLCOMING Department, University of Sassari, 07100 Sassari, Italy (e-mail: gpaolini@uniss.it).

A. Mirelman and J. M. Hausdorff are with the Movement Disorders Unit, Department of Neurology, Tel Aviv Sourasky Medical Center, 64239 Tel Aviv, Israel (e-mail: jhausdor@tlvmc.gov.il).

S. Gaukrodger is with Inition Ltd, EC2A 3LT London, U.K.

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TNSRE.2013.2282868

segments, if the full body is not visible to the Kinect camera. This requirement leads to several technical limitations. First, the need for including a full human body limits the measurement resolution of isolated body segments motion. Second, the motion of the skeleton is successfully tracked only if the segmented skeleton image is not obstructed or distorted by the presence of objects either placed between the Kinect and the subject or attached to the subject.

To our knowledge, only a few studies have employed the Kinect technology without using the whole body movement tracking tool provided with the system. Dutta *et al.* investigated the use of the Kinect as a portable motion capture system. The relative position between static objects captured with the Kinect and a multi-camera system was estimated and compared [13]. The results indicated that the accuracy of the Kinect in static conditions was about 10 mm, within a range of 1–3 m from the sensor.

In a recent report, Mirelman *et al.* presented a VR-based gait training program in which the subjects had to negotiate virtual obstacles while walking on a treadmill [4]. During the training, virtual shoes reproducing the subject's feet motion were presented to the user as real time visual feedback for performance in the virtual environment. The tracking methodology used in the study, based on optoelectronic technology, showed some limitations, i.e.,, space, cost, and calibration procedures to be performed. To overcome such limitations, we developed an alternative motion tracking method with the goal of preserving the quality of foot motion tracking during treadmill walking, using the Microsoft Kinect for Windows (Microsoft, Redmond, WA, USA) and colored markers. The method is based on a custom procedure that exclusively tracks foot motion, without using the built-in skeleton tracking tool, to be transferred to a pair of virtual shoes integrated in the virtual environment. This approach is currently being used in a multi-modal rehabilitation intervention that is designed to test whether treadmill training combined with VR enhances mobility and reduces fall risk in a large sample of elderly fallers, patients with Parkinson's disease and individuals with mild cognitive impairment [14]. Hereby, we report on a validation study aimed at assessing the accuracy of this new method of tracking and validating it against the gold standard SP system.

II. Methods

A. Set-Up

To increase video camera white balance control setting capabilities, the Kinect RGB camera was replaced by a different, low cost RGB camera (Microsoft LifeCam Studio, 1080p HD) glued on top of the Kinect. The alternative RGB camera was used to fully manually control the image parameters as opposed to the Kinect's built in video camera, which automatically sets the image parameters making the extraction of the 2-D colored markers more sensitive to lighting and background conditions, thus affecting the mapping with depth data to create the 3-D data. To integrate the video images produced by the RGB camera with the information provided by the depth sensor, a stereo calibration procedure was carried out [15]. The resulting system composed by RGB video and depth sensing (RGB-D

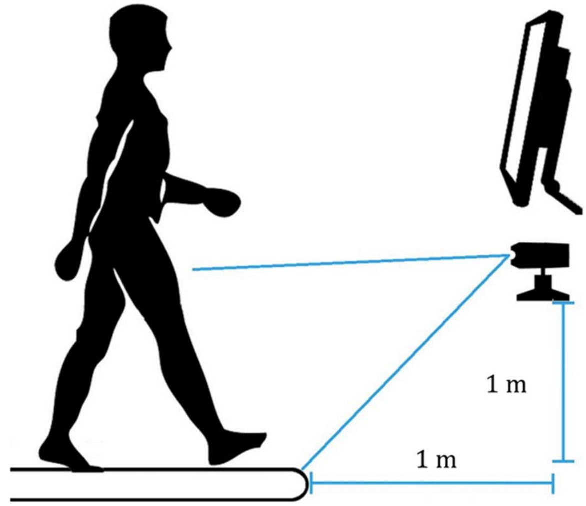


Fig. 1. Configuration of the system: a subject walking on a treadmill while looking at a monitor where a VR-based gait training program is delivered.

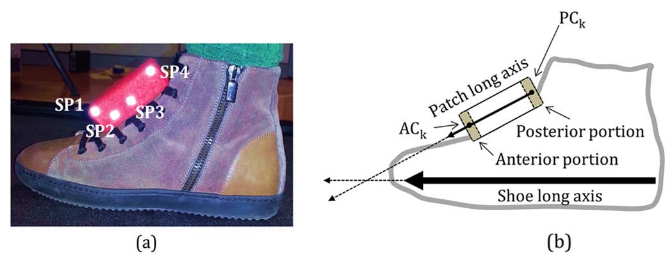


Fig. 2. The 3-D patch is positioned over the shoe with the four flat markers on it (marked as SP1-SP4) (a). Anterior and posterior portions of the 3-D patch are highlighted. Centroids $\mathrm{AC_k}$ and $\mathrm{PC_k}$ are identified. Axes of the 3-D patch and foot are also shown (b).

system), was placed 1 m above the ground and 1 m in front of the treadmill (which is within the range of operation of the depth sensor of the Kinect [16]) so that it had an unobstructed view of the treadmill belt surface (Fig. 1). The RGB-D system captured data at a nominal sampling rate of 30 fps.

A six-camera (2 MPixel, 50 fps) SP system (Vicon, Oxford Metrics, Oxford, U.K.) was used for validation purposes (position error <1 mm, angular error $< 1°$). The two systems were given the same, synchronous remote start signal using a switch that connected between them. The motion of a single foot on each subject was considered for this validation study. A colored 3-D patch $(80\ \mathrm{mm} \times 30\ \mathrm{mm} \times 25\ \mathrm{mm})$ was firmly attached to the left shoe by aligning its long side with the foot's sagittal plane [Fig. 2(a)]. Four flat retro-reflective markers (6 mm diameter), to be tracked by the SP system, were applied laterally on the 3-D patch without affecting the performance of the RGB-D tracking.

B. Tracking Procedure

The RGB image is first converted to its corresponding image in the HSV color space, and then filtered according to the color to detect (e.g., red). The result is a binary image of black background and white pixels in correspondence of the colored 3-D patch. Before each experimental session, a quality check is performed on the color-filtered image to ensure that the image of

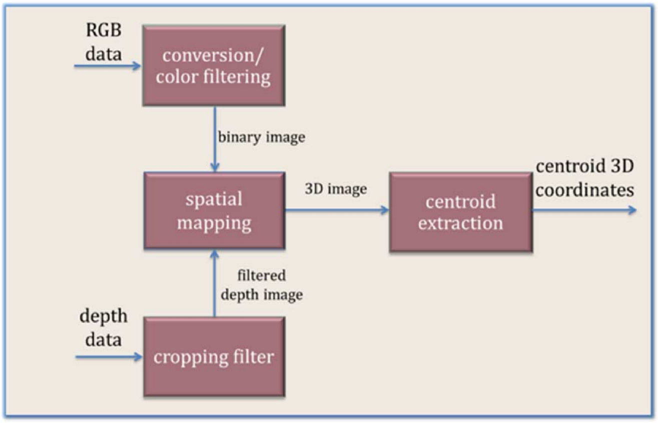


Fig. 3. Flowchart of the RGB-D tracking methodology for the extraction of the anterior and posterior colored patch centroids.

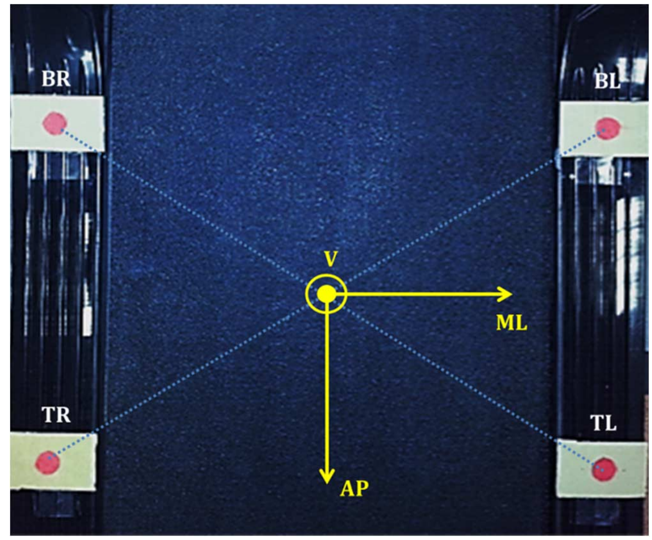


Fig. 4. CCS. Origin: Located in the midpoint of the four points. X-axis: From the origin to midpoint of segment BL-TL, pointing to the right of treadmill (ML: medio–lateral direction). Y-axis: Perpendicular to the treadmill plane, pointing up (V: vertical direction). Z-axis: Defined by the cross product of the unit vectors of the X- and Y-axes, pointing to the back of the treadmill (AP: anterior–posterior direction).

the patch as extracted by the color filter is solid. This is done using a custom-made software application allowing the operators to modify the image parameters (i.e., brightness, hue, saturation) according to the quality of the filtered image. A cropping filter with adjustable parameters is then applied to isolate the region of interest (RoI) from the depth image, to reduce the detrimental effects of the background on tracking quality and processing time; for the purpose of the current study, the RoI was identified once for all the subjects, before the beginning of the experimental sessions. For each instant of time, the length of the patch is computed from the filtered image and the most anterior and posterior portions of the patch (10% of the total patch length each) are isolated. The centroids $\mathrm{AC_K}$ and $\mathrm{PC_K}$ of the white pixels belonging to the anterior and posterior portions respectively are then computed (Fig. 3). From the reconstructed position of the two centroids, an oriented segment (AC-PC), with the origin centered in $\mathrm{PC_K}$ and passing through $\mathrm{AC_K}$, is determined. Under the assumption that both the 3-D patch and the foot are rigid bodies, the geometrical relationship between the patch and foot axes can be considered time-invariant [Fig. 2(b)].

C. Participants and Data Collection

Twelve healthy subjects (five females, age: 32 ± 5 years, height: 1.73 ± 0.09 m, mass: 72 ± 15 kg), with no history of neurological or orthopedic condition or medication use influencing their motor control, were included in this study.

Participants walked on a treadmill at a comfortable speed (3 km/h), under three conditions:

1) natural walking (normal);
2) walking with vertical virtual obstacles (high);
3) walking with long horizontal virtual obstacles (long).

For each subject, a static trial was captured at the beginning and at the end of the acquisition session. A single 30-s trial was captured for each gait condition.

D. Data Analysis

To compare the performance of the RGB-D system with the SP system, a common coordinate system (CCS) was defined, using four points located on the treadmill surface (TR, BR, BL, TL—Fig. 4), visible to both systems.

During the static trials, the centroid coordinates $\mathrm{AC_K}$ and $\mathrm{PC_K}$ provided by the RGB-D system and the coordinates of the four retro-reflective markers (SP1, SP2, SP3, SP4), as measured by the SP system, were expressed in the CCS. Using the retro-reflective markers, an auxiliary coordinate system embedded to the 3-D patch was defined. The positions of $\mathrm{AC_K}$ and $\mathrm{PC_K}$ with respect to the auxiliary coordinate system were then computed and used to define the time-invariant relationship between the retro-reflective markers and the 3-D patch centroids [17]. During the gait trials, from the measured retro-reflective markers positions expressed in the CCS and exploiting the information provided by the abovementioned static calibration procedure, it was then possible to generate the trajectories of the anterior and posterior patch centroids $\mathrm{AC_S}$ and $\mathrm{PC_S}$ as provided by the SP system (gold standard).

Since the RGB-D system does not provide data at a constant sampling rate, the recorded time histories of the centroid coordinates were linearly interpolated to obtain time histories resampled at 30 fps. The position data from the SP system was also resampled at 30 fps. To limit the effects of the image noise, the coordinates of $\mathrm{AC_K}$ and $\mathrm{PC_K}$, as extracted by the RGB-D system, were filtered with a fourth-order, low-pass Butterworth filter (cut off frequency: 8 Hz).

The position of the segment 3-D patch can be uniquely determined by the coordinates of its origin (AC), while the description of its orientation can be limited to the determination of a single direction since only two points (AC and PC) are used to identify the patch. Therefore, the components of the 3-D patch unit vector ($\overline{\mathrm{AC} - \mathrm{PC}}$ unit vector) expressed in the CCS were used to describe the patch orientation. For the different walking conditions analyzed, the consistency of the 3-D patch positions estimated by the two systems was evaluated both in terms of offset and pattern dissimilarity. The *Offset* was calculated as the absolute difference between the mean values of

TABLE I
AVERAGE VALUES AND STANDARD DEVIATIONS (OVER 12 SUBJECTS) OF THE *Offset*, $RMSD$ AND ΔRoM OF THE 3-D PATCH ORIGIN POSITION, AS ESTIMATED BY THE RGB-D AND BY THE SP SYSTEMS, IN THE THREE WALKING CONDITIONS. MEASUREMENTS ARE IN mm

Walking Condition	*Offset* [mm]			*RMSD* [mm]			*ΔRoM* [mm]		
	ML	V	AP	ML	V	AP	ML	V	AP
Normal	4.7±2.1	0.7±3.7	8.2±8.5	4.9±1.4	8.4±1.7	19.4±6.1	0.6	7.0	51.8
Long	4.1±3.0	0.6±4.0	7.7±10.3	5.7±1.7	9.3±2.8	22.0±11.0	1.8	3.6	65.9
High	6.0±3.3	0.0±4.2	9.9±11.1	6.4±1.6	12.1±4.5	26.5±9.1	4.5	3.4	71.8

TABLE II
AVERAGE VALUES AND STANDARD DEVIATIONS (OVER 12 SUBJECTS) OF THE %RMSD OF THE 3-D PATCH UNIT VECTOR COMPONENTS AS ESTIMATED BY THE RGB-D AND BY THE SP SYSTEMS IN THE THREE WALKING CONDITIONS

Walking Condition	*%RMSD*		
	ML	V	AP
Normal	5.6±1.3	7.9±2.6	15.5 ± 5.7
Long	6.5±1.5	8.7±2.8	16.8 ± 6.3
High	7.3±2.3	8.8±3.5	18.6 ± 8.1

the 3-D patch position averaged over the trial duration obtained with the RGB-D system and those obtained with the SP system. The pattern dissimilarity was assessed calculating the root mean square deviation ($RMSD = \sqrt{\Sigma_{i=0}^{n}(y_i - y_i')^2/n}$, where y_i and y_i' represent the value of the variable at time i aligned to the respective mean for the RGB-D and the SP system, respectively) of time histories obtained with the RGB-D and the SP systems aligned to their respective mean values. The correlation coefficient (R) and absolute difference between the 3-D patch range of motion (ΔRoM) estimated with the RGB-D system and that estimated with the SP system, were also evaluated. Differences in the 3-D patch orientation, as estimated by the two systems, were expressed in terms of mean percentage of the root mean square deviation ($\%RMSD = RMSD/RoM\%$, where RoM represents the maximum variation of the relevant variable estimated using the SP system) of the unit vector components obtained with the RGB-D system with respect to those obtained with the SP system. The relevant R values were also determined.

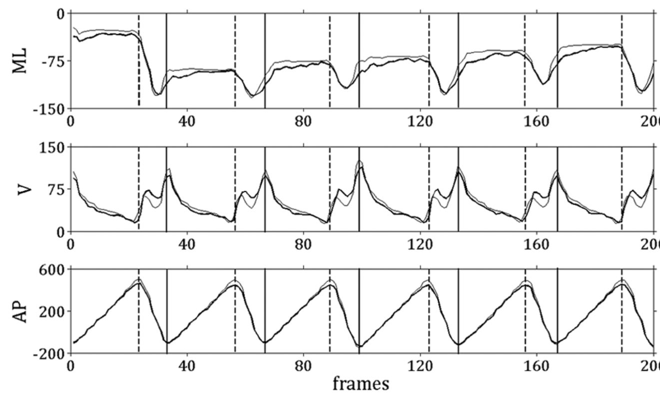


Fig. 5. 3-D patch origin position (ML, V, and AP, in mm), as recorded by the RGB-D (thick lines) and by the SP (thin lines) systems, during six gait cycles of a representative gait trial (normal condition). Curves are aligned to their respective mean values. Vertical solid/dashed lines: heel strike/toe off.

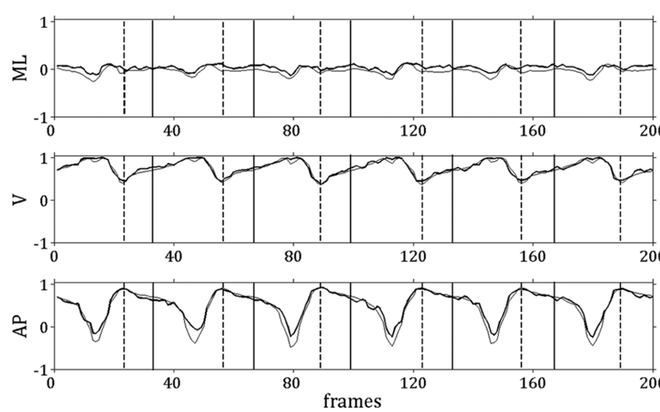


Fig. 6. Components of the 3-D patch unit vector representing the direction of 3-D patch as obtained from the RGB-D (thick lines) and the SP (thin lines) systems during six gait cycles of a representative gait trial (normal condition). Vertical solid/dashed lines: heel strike/toe off.

III. RESULTS

The average and standard deviations of the *Offset*, $RMSD$ and ΔRoM of the 3-D patch origin position as estimated by the RGB-D and SP systems, for the three walking conditions amongst all subjects, are reported in Table I. The relevant R values varied from 0.93 to 0.99 in the three directions.

The average and standard deviations of the $\%RMSD$ of the components of the 3-D patch unit vector as estimated by the RGB-D and the SP systems for the three walking conditions amongst all subjects, are reported in Table II.

The average R values for the components of the 3-D patch unit vector ranged from 0.85 to 0.9 across walking conditions for the AP and V directions, while they ranged from 0.53 to 0.63 for the ML direction.

The 3-D patch origin position time histories of a representative normal walking trial as estimated by the SP and RGB-D systems are reported in Fig. 5. The time histories of the 3-D patch unit vector components obtained for the same six cycles of the same trial are reported in Fig. 6.

IV. Discussion

The Kinect is a motion tracking device, composed of an RGB camera and a depth sensor (RGB-D sensor). A software tool for full human body tracking is provided with the device. In this study, a new method for tracking foot motion with a RGB-D sensor without using the built-in full body tracking tool is presented for tracking foot motion during gait training on a treadmill during three different walking conditions. Tracking the foot motion without using the built in full body motion tracking tool allows for focusing on a smaller measuring volume, thus making the experimental setup more flexible and, possibly, provide better tracking of the foot motion. We validated the method against simultaneous tracking obtained with a stereo-photogrammetric (SP) system.

The position of the 3-D patch was tracked with limited errors in the frontal plane, which is almost parallel to the camera sensor plane (both *Offset* and $RMSD$ average values smaller than 13 mm). The errors were larger in the depth coordinate (AP direction) (average $RMSD$: 26.5 ± 9.1 mm); in particular, the maximum error was observed at toe-off, when the foot is at its farthest point from the RGB-D sensor. This was expected, given the characteristics and technical specifications of the depth sensor [10]. Nevertheless, the correlation between the RGB-D and the SP estimates were excellent $(R > 0.9)$ not only in the ML and V directions but also in the AP direction (Fig. 5). Consequently, such errors in the AP direction may not affect the subject experience of the virtual environment. The errors along the V direction were similar (average *offset* values lower than 0.7 mm, average $RMSD$ between 8.4 and 12.1 mm) amongst the three conditions analyzed. Therefore, the system appears to be capable of tracking obstacle negotiation in both vertical (requiring a higher step) and horizontal (requiring longer steps) planes.

Since the foot was identified with an oriented direction vector (only two foot points were tracked), the determination of its orientation was possible only in terms of components of its unit vector in the CCS. The differences in the estimates obtained from the two motion tracking systems were quantified by the mean $\%RMSD$ values of the above mentioned unit vector components. As expected the errors of the AP component were the largest. Looking at the representative pattern of the AP component (Fig. 6), the largest discrepancy appears to be just before toe off (instances of minimum values). However the high mean R values found for the unit vector components (from 0.86 to 0.88) limit the relevance of such errors, since they can guarantee an effective reproduction of the foot motion in the virtual environment.

In conclusion, the combined use of the RGB-D technology and the motion tracking method proposed in this study can be successfully used for generating an effective reproduction of the feet motion in the virtual environment to be used as feedback of the subject undergoing a VR and treadmill gait training program. Preliminary results indicate that the combined use of VR environments and a treadmill improves gait and mobility in patients with neurological impairments. To maximize the effects of such training, feedback of the subject's movement should be included in the virtual environment. Reproducing the feet motion in the virtual environment may be an appropriate choice [4]. To ensure realism of the feet movement reproduced in the virtual environment, it is crucial to obtain good estimates of both its position and orientation. The proposed system appears to effectively address these needs. Additional positive aspects of the proposed solution are its low cost and low obtrusiveness, which can facilitate its use in clinical environments.

Furthermore, the methodology presented here has the potential to be applied to the tracking of body segments during different motor tasks, if a 3-D patch can be applied to each segment under analysis. However, since the level of accuracy depends on the patch size, its distance from the RGB-D sensor, and on the motion to track, an accuracy assessment is necessary for each different application. Moreover, it is important to highlight that the present methodology has been validated on healthy subjects and the performance of the foot motion tracking methodology might differ when considering patient populations affected by extreme out-toeing or drop foot during walking.

References

[1] M. K. Holden, "Virtual environments for motor rehabilitation: Review," *CyberPsychol. Behav.*, vol. 8, no. 3, pp. 187–211, 2005.

[2] S. H. You, S. H. Jang, Y. H. Kim, M. Hallett, S. H. Ahn, Y. H. Kwon, J. H. Kim, and M. Y. Lee, "Virtual reality-induced cortical reorganization and associated locomotor recovery in chronic stroke: An experimenter-blind randomized study," *Stroke*, vol. 36, no. 6, pp. 1166–1171, Jun. 2005.

[3] J. Fung, C. L. Richards, F. Malouin, B. J. Mcfadyen, and A. Lamontagne, "A treadmill and motion coupled virtual reality system for gait training post-stroke," *CyberPsychol. Behav.*, vol. 9, no. 2, pp. 157–163, 2006.

[4] A. Mirelman, I. Maidan, T. Herman, J. E. Deutsch, N. Giladi, and J. M. Hausdorff, "Virtual reality for gait training: Can it induce motor learning to enhance complex walking and reduce fall risk in patients with Parkinson's disease?," *J. Gerontol. Ser. A, Biol. Sci. Med. Sci.*, vol. 66, no. 2, pp. 234–240, Feb. 2011.

[5] D. Périé, A. J. Tate, P. L. Cheng, and G. A. Dumas, "Evaluation and calibration of an electromagnetic tracking device for biomechanical analysis of lifting tasks," *J. Biomechan.*, vol. 35, no. 2, pp. 293–297, Mar. 2002.

[6] R. Best and R. Begg, "Overview of movement analysis and gait features," in *Computational Intelligence for Movement Science: Neural Networks and Other Emerging Techniques*. Hershey, PA: Idea Book, 2006, ch. 1.

[7] Y. K. Thong, M. S. Woolfson, J. A. Crowe, B. R. Hayes-Gill, and D. A. Jones, "Numerical double integration of acceleration measurements in noise," *Measurement*, vol. 36, no. 1, pp. 73–92, Jul. 2004.

[8] A. Peruzzi, U. Della Croce, and A. Cereatti, "Estimation of stride length in level walking using an inertial measurement unit attached to the foot: A validation of the zero velocity assumption during stance," *J. Biomechan.*, vol. 44, no. 10, pp. 1991–1994, 2011.

[9] P. Picerno, A. Cereatti, and A. Cappozzo, "A spot check for assessing static orientation consistency of inertial and magnetic sensing units," *Gait Posture*, vol. 33, pp. 373–378, 2011.

[10] K. Khoshelham and S. O. Elberink, "Accuracy and resolution of Kinect depth data for indoor mapping applications," *Sensors*, vol. 12, no. 2, pp. 1437–1454, Jan. 2012.

[11] C. Y. Chang, B. Lange, M. Zhang, S. Koenig, P. Requejo, N. Somboon, A. Sawchuk, and A. Rizzo, "Towards pervasive physical rehabilitation using Microsoft Kinect," in *Proc. 6th Int. Conf. Pervasive Comput. Technol. Healthcare*, 2012, pp. 2–5.

[12] R. A. Clark, Y.-H. Pua, K. Fortin, C. Ritchie, K. E. Webster, L. Denehy, and A. L. Bryant, "Validity of the Microsoft Kinect for assessment of postural control," *Gait Posture*, vol. 36, no. 3, pp. 372–377, Jul. 2012.

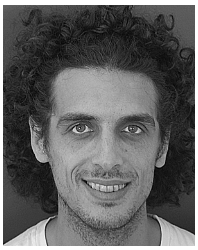
[13] T. Dutta, "Evaluation of the Kinect sensor for 3-D kinematic measurement in the workplace," *Appl. Ergonom.*, vol. 43, no. 4, pp. 645–649, Jul. 2012.

[14] A. Mirelman, L. Rochester, M. Reelick, F. Nieuwhof, E. Pelosin, G. Abbruzzese, K. Dockx, A. Nieuwboer, and J. M. Hausdorff, "V-TIME: A treadmill training program augmented by virtual reality to decrease fall risk in older adults: Study design of a randomized controlled trial," *BMC Neurol.*, vol. 13, no. 1, p. 15, Feb. 2013.

[15] Z. Zhang, "A flexible new technique for camera calibration," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 22, no. 11, pp. 1330–1334, Nov. 2000.

[16] Interaction space [Online]. Available: http://msdn.microsoft.com/en-us/library/hh973071.aspx

[17] A. Cappozzo, F. Catani, U. Della Croce, and A. Leardini, "Position and orientation in space of bones during movement: Anatomical frame definition and determination," *Clin. Biomechan.*, vol. 10, no. 4, pp. 171–178, 1995.



Gabriele Paolini received the M.S. degree in electronic engineering from the University of Bologna, Bologna, Italy, in June 2003.

He works as a Research Associate at the University of Sassari, Sassari, Italy. His research interests are in the biomechanics of human motion and its measurement techniques.

Agnese Peruzzi graduated in biomedical engineering from the Rome Campus Biomedico University, Rome, Italy, in 2009, and received the Ph.D. degree in bioengineering from the University of Bologna, Bologna, Italy, in 2013.

She is currently a Research Associate at the University of Sassari, Sassari, Italy. Her research interests include quantitative analysis of human movement based on virtual reality, video and magneto-inertial sensor technology.

Anat Mirelman received the Ph.D. degree in 2007 focused on technology for treatment of gait disorders from the University of Medicine and Dentistry of New Jersey (UMDNJ), NJ, USA.

She works at Tel Aviv Sourasky Medical Center, Tel Aviv, Israel, investigating motor and cognitive function in neurodegenerative disorders and developing innovative technology to enhance function. She is affiliated with Ben Gurion University and Harvard Medical School.

Andrea Cereatti graduated in mechanical engineering from Roma Tre University, Rome, Italy, in 2002, and received the Ph.D. degree in bioengineering from the University of Bologna, Bologna, Italy, in 2006.

He currently works as an Assistant Professor of Biomedical Engineering at the University of Sassari, Sassari, Italy. His research interests include biomechanics of human movement, joint modelling, orthopaedics engineering, and ambulatory monitoring based on magneto-inertial sensor technology.

Stephen Gaukrodger is a New Zealand born software engineer, currently living in London, U.K. He has a background in computer vision, augmented reality, perceptual psychology, rehabilitation, and air traffic control.

Jeffrey M. Hausdorff is the Director of the Laboratory for the Analysis of Gait and Neurodynamics at Tel-Aviv Sourasky Medical Center, Tel-Aviv, Israel, Professor at the Sackler Faculty of Medicine, New York, NY, USA, and Lecturer in Medicine at Harvard Medical School, Boston, MA, USA. He investigates gait, balance, motor control, and motor-cognitive interactions in health and disease.

Ugo Della Croce is full Professor at the University of Sassari, Sassari, Italy. His research is mainly focused on methods to improve quantitative human movement measurements, including video, dynamometry, and inertial sensing. He is author of more than 80 international publications and held about 20 invited lectures and seminars in the field of analysis of human movement in various European and Northamerican institutions.

Dr. Della Croce is President elect of SIAMOC (Italian Society of Human Movement Analyis).