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Robotics-Driven Gait Analysis: Assessing Azure Kinect's Performance in In-Lab versus In-Corridor Environments

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Abstract

Gait analysis offers vital insights into human movement, aiding in the diagnosis, treatment, and rehabilitation of various conditions. Analyzing gait in corridors, rather than in lab, provides unique advantages for a more comprehensive understanding of human locomotion. However, limited dedicated technologies constrain gait data analysis in this context. In this study, a markerless gait analysis system using an Azure Kinect sensor mounted on a mobile robot is proposed and validated as a potential solution for gait analysis in corridors. Ten healthy participants (4 males, 6 females) underwent two tests. The first test (5 trials per participant) took place in the laboratory. Here, Azure Kinect performance was validated against a Vicon® system, assessing eight gait signals and 22 gait parameters. The second test (2 trials per participant) was performed in the corridors over a 32-meter walking distance in order to compare this gait pattern with the one developed within the laboratory. The intrasession ICC reliability for in-lab experiments was assessed by calculating the Intraclass Correlation Coefficient (ICC) between gait cycles captured in each session per participant. Notably, knee flex./ext. (ICC-0.95), hip flex./ext. (ICC-0.96), pelvis rotation (ICC-0.88), and inter-ankle distance (ICC-0.98) demonstrated excellent reliability with high confidence. Similarly, hip add./abd. showed good reliability (ICC-0.79), while trunk rotation exhibited moderate reliability (ICC-0.72). In contrast, both trunk tilt (ICC-0.24) and pelvis tilt (ICC-0.41) consistently displayed lower reliability. This was observed for both the Vicon and the Azure systems, highlighting the intricate nature of capturing precise data for these specific signals in both systems. Validity outcomes indicated comparable error rates to literature standards (12.68° knee flex./ext., 5.54° hip flex./ext., 3.45° hip add./abd.), with 11 parameters having no significant differences from Vicon®. Comparison of in-lab and in-corridor experiments show that individuals exhibit significantly longer stride time (1.10s vs. 1.05s), lower pelvis tilt (6.83° vs. 9.39°) and lower minimum pelvis rotation (-5.82° vs. -14.61°) when walking in laboratory. This study demonstrates promising outcomes in outdoor gait analysis with a robot-mounted camera, revealing significant distinctions from controlled laboratory evaluations

KEYWORDS
Mobile robot, gait analysis, depth sensors

1 | INTRODUCTION

Gait analysis is a valuable tool used across several domains, including rehabilitation, biomechanics, and clinical diagnostics focused on neurological or muscular disorders[1]. It can be performed through different methodologies, such as visual observation, instrumented analysis, and computerized analysis[2]. Among instrumented analysis methods, photogrammetric motion capture systems have been widely used due to their ability to provide detailed kinematic and spatiotemporal features of human movement. However, several issues like marker displacement, limited field of view, lighting conditions, expensive equipment, and time-consuming data processing are associated with photogrammetric systems for gait analysis[3]. While

Abbreviations: GEE, Generalized Estimating Equations; RGBD, Red Green Blue-Depth; SLAM, simultaneous localization and mapping; IMU, inertial measurement unit; TEB, Timed Elastic Band; ROS, Robot Operating System.

they offer valuable information, these systems present limitations requiring careful consideration for research or clinical purposes[4].

Recent advancements in artificial intelligence and computer vision have paved the way for automated pose estimation algorithms utilizing simple 2D videos captured by RGB cameras. Notable examples include OpenPose[5], TensorFlow MoveNet[6], Yolo-pose[7], DeepLabCut[8], MediaPipe Pose[9] and BlazePose[10]. Despite the increasing body of literature on the development and validation of these algorithms (like in the study presented by Washabaugh et al.[11]), their adoption by health professionals remains limited. Manual video annotation tools continue to be prevalent, partly due to the occasional unpredictability and error-proneness of pose estimation modules from 2D videos. Health professionals tend to favor established marker-based technologies like Vicon®, while sport specialists often use methods from manual video annotation tools designed for biomechanics, such as Kinovea[12].

More recently, motion capture based on 3D video from RGBD cameras, particularly sensors like Azure Kinect, has emerged as a promising tool in both research and clinical applications for gait analysis[13,14,15]. Studies have systematically evaluated Azure Kinect's validity and reliability against other motion capture systems, highlighting its potential across diverse configurations and applications. For example, Trent et al.[13] conducted a comparison between Azure Kinect and a 12-camera Vicon® system for overground walking analysis, assessing spatiotemporal parameters in 21 healthy participants. Their findings underscored Azure Kinect's ability to provide clinically relevant measurements, reporting errors of 35.6 mm for stride length, 10 ms for stride time, 28.6 mm for step length, and 3.7 mm for step width.

In the work of Ling et al.[14], the effects of camera viewing angles on tracking kinematic gait patterns were explored using Azure Kinect, Kinect v2, and Orbbec Astra Pro v2. This investigation, conducted with a static camera setup during treadmill walking, highlighted Azure Kinect's superior tracking performance. The authors attributed this to Azure Kinect's enhanced depth sensor resolution and body tracking algorithm, especially for hip and knee flexion/extension joint angles in non-frontal captures.

Yunru et al.[15] used a dual Azure Kinect system to analyze gait information from five healthy participants. Joint angle results were compared with those acquired by a Vicon® system, reporting errors of 11.9° for knee flexion/extension, 15.1° for hip flexion/extension, and 7.2° for hip adduction/abduction, generally lower than observed with a single Kinect V2. These comparative studies have shown Azure Kinect's favorable accuracy, displaying lower overall errors compared to other depth sensors tested for gait analysis and good accuracy compared to photogrammetric systems. Consequently, such sensors could pave the way for more flexible, reliable, and cost-effective treatment plans[16].

This study emphasizes the exploration of Azure Kinect cameras over conventional 2D video-based RGB cameras, highlighting their distinctive capabilities. Azure Kinect cameras, which integrate depth information with RGB, offer the potential for a more detailed analysis of human movement. In contrast to 2D video-based systems, Azure Kinect cameras have the capability to capture three-dimensional data, potentially enhancing the accuracy and reliability of pose estimation and gait analysis. This work aims to extend the evaluation of Azure Kinect in gait analysis to a robot-mounted camera scenario, offering advantages over traditional static camera setups, especially in larger acquisition ranges and real clinical settings[17]. The experimental section includes two types of tests: the first in the laboratory (5 trials per participant) validating Azure Kinect against a Vicon® system on eight gait signals and 22 gait parameters, and the second in corridors over a 32-meter walking distance to compare gait patterns developed in the laboratory.

The results have shown an encouraging accuracy and correlation for hip flexion/extension and hip adduction/abduction, moderate accuracy for pelvis tilt, trunk rotation, and pelvis rotation, and low correlation for trunk tilt, potentially due to time delays between signals from differences in biomechanical models. The accuracy and correlation of other points like knee flexion/extension, inter-ankle distance were also analyzed and compared against a Vicon® system. The overall error for the robot-mounted camera configuration aligns closely with literature values using static sensors and treadmills for gait assessment. This validates the proposed configuration, ensuring no influence from camera motion. Moreover, 11 out of 22 gait parameters measured by Azure Kinect show no significant differences compared to the Vicon® system. The comparison of both tests reveals individuals exhibiting significantly longer stride time, lower pelvis tilt, and lower minimum pelvis rotation in laboratory walking, supporting the proposed outdoor configuration due to differing walking patterns in controlled laboratory versus real-life environments.

The subsequent sections delve into an in-depth exploration of the applied methodology and describe the mobile robot subsystem (Section 2.1), body tracking subsystem (Section 2.2), the performance evaluation (Section 2.3), obtained results (Section 3), comparisons with existing work, and conclusions (Sections 4 and 5).

2 | METHODS

The proposed gait analysis system comprises a mobile robotic platform along with an Azure Kinect sensor that utilizes the Azure Kinect Skeleton Tracking SDK from Microsoft for motion capture. The subsequent sections will detail the mobile

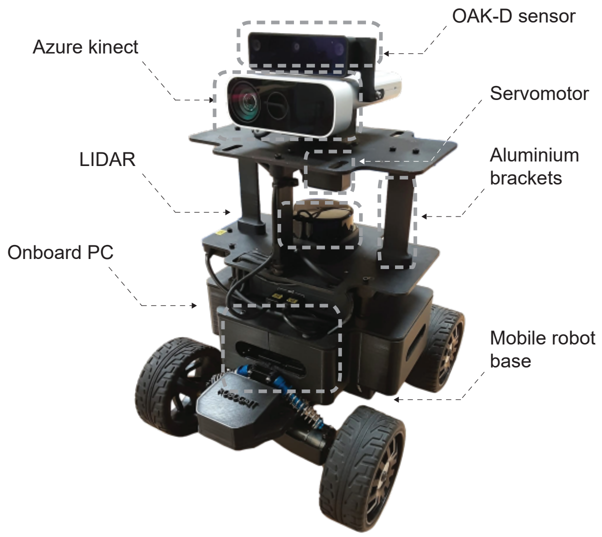

FIGURE 1 An overview of the Mobile robotic platform designed in this study.

robot subsystem, the body tracking subsystem description and the performance evaluation methodology.

2.1 | Mobile Robot Description

The objective of the mobile robotic platform was to perform gait assessment in real-world environments, similar to those present in typical clinical settings. For this purpose, it was necessary to design and incorporate specific components of hardware and software. Fig. 1 shows the main components of the mobile robotic platform. Each of them is described below:

- **Azure Kinect sensor:** It is in charge of the body tracking task. To reduce processing requirements, gait movements are recorded during the experiments, but skeleton information is retrieved offline. An online processing would require the use a of dedicated GPU [18], thus, highly increasing the power consumption, the mass and size of the system.
- **Onboard PC:** It consists on an Intel NUC with an Intel Core i7 processor. It hosts a ROS2 operating system that manages system communication, mapping, navigation, path planning, and video recording among others. During the offline processing of the data from the Azure camera, it takes approximately 5 minutes to process every recorded minute of walking test.
- **Lidar:** This sensor is used to collect information for slam and navigation purposes.
- **IMU:** Together with the wheel encoders and lidar, IMU data is used to estimate the robot's odometry.
- **Servomotor:** Its purpose is to rotate the Azure Kinect and OAK-D cameras towards the person's location to obtain a proper capture.
- **OAK-D sensor:** The OAK-D is a stereo-depth camera used to track the person's position during experiments. This information is required for the person following action.

In addition, it is worth mentioning that the mobile robot has a differential drive configuration weighing 10 kg, with a maximum speed of 1.2 m/s and an autonomy of 2 hours. Furthermore, the OAK-D camera is a stereo arrangement that does not allow having a direct measure of the depth contrasting to the Azure Kinect; therefore, we relegate the OAK-D camera just for the person tracking instead of offline gait analysis.

2.1.1 | Robot Communication

In order to manage system data processing, an onboard computer is mounted on the robot. The onboard computer runs a 64-bit Ubuntu Linux-Focal Fossa (20.04) operating system and also hosts the Robot Operating System (ROS). ROS is an open-source software framework used for developing robotics software. It provides a collection of tools, libraries, and conventions that developers use to create complex and robust robot applications. A ROS2 Foxy Fitzroy version was used. ROS2 is a complete overhaul of the original ROS framework with improved real-time performance, better support for multi-robot systems and improved security. The functional diagram of the system is shown in Fig. 2.

2.1.2 | Robot Localization and Control

NAV2 is a navigation stack that is commonly used in ROS2 for autonomous mobile robots. One of the key features of NAV2 is its ability to fuse data from multiple sensors, such as wheel encoders and lidar, to estimate the robot's odometry (position and orientation) in the environment.

In the robotic system presented in this study, the Extended Kalman Filter (EKF) algorithm in NAV2 is used to fuse data from wheel encoders, IMU and lidar. The EKF algorithm combines the information from these sensors to estimate the robot's position. The algorithm takes into account the uncertainties associated with each sensor and calculates a weighted average of the estimates to obtain a more accurate and reliable pose estimate.

To implement the path planning capability on the robot, TEB Local Planner for ROS2 was used [19]. TEB stands for Timed Elastic Band, which is an optimization-based trajectory planning algorithm. In the robotic platform presented in this study, the local plan provided by the TEB local planner is sent to

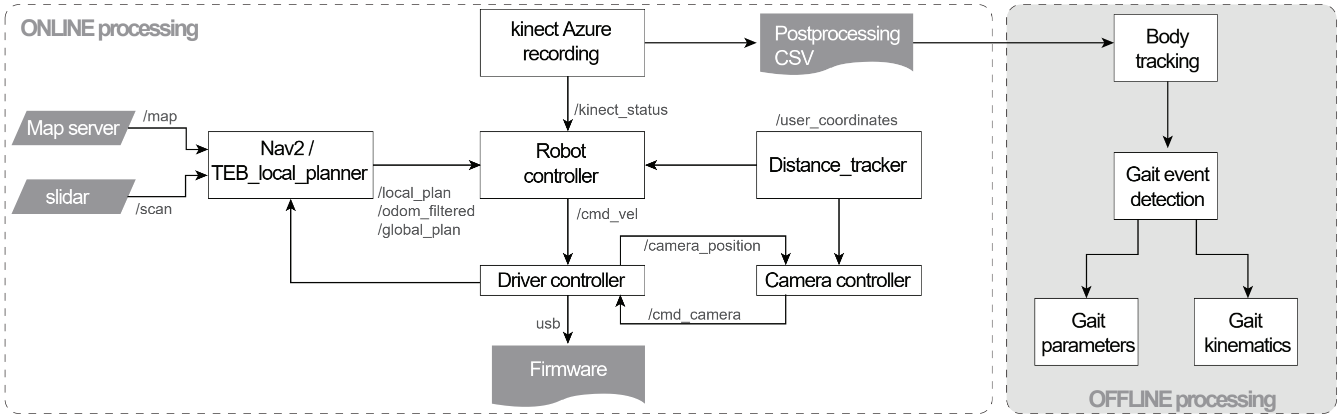

FIGURE 2 A schematic of the control architecture implemented in the system.

the robot controller for obstacle avoidance and the global plan coming from NAV2 is used to set the experimental trajectory.

Once the robot is localized in the environment and path planning is executed, the next step is to set the control strategy to move the robot. The primary actors in robot control are the experimental trajectory and the individual whose gait pattern is being assessed. On this basis, the robot controller is designed to follow a preplanned trajectory while keeping a constant distance from the person. Therefore, a double controller is applied, one for the person following, and the other for lane keeping.

Fig. 3 shows the data used by the system during a navigation experiment. The set point for the lane-keeping controller is the steering angle (${}^{F_M}\theta_s$). This is the angular position in the map frame (F_M) of the relative vector joining the third point in the local plan and the center of the robot. The error entering in the controller is obtained by comparing the orientation of the robot in the map frame (${}^{F_M}\theta_r$) and the steering point as follows:

$$ {}^{F_M}\theta_{error} = {}^{F_M}\theta_s - {}^{F_M}\theta_r \quad (1)$$

For the person following, the set point was set at 3 meters and the actual distance was measured using the OAK-D sensor, located just above the Azure Kinect. This sensor provides the ${}^{F_c}X_p$ and ${}^{F_c}Y_p$ positions of the person in the camera frame (F_C). By calculating the distance to the person in the camera frame (${}^{F_c}P_p$) is possible to find the error of position for the person following the controller using the formula:

$$ {}^{F_c}P_{error} = 3 - {}^{F_c}P_p \quad (2)$$

The angular position of the person in the camera frame (${}^{F_c}\theta_p$), allows a continuous rotation of the camera to align it with the person. The process followed for tuning both controllers and analyzing their performance is detailed in [20,21].

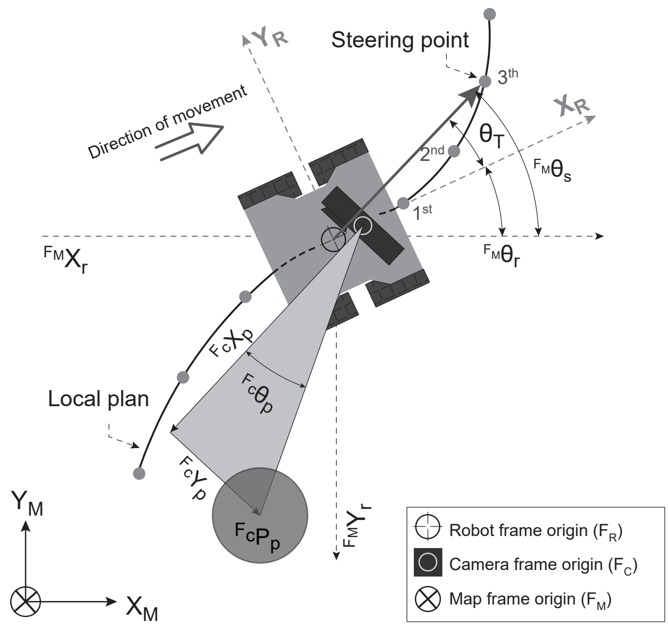

FIGURE 3 Reference frames used in the robot control

2.2 | Body Tracking Subsystem

Body tracking utilized an Azure Kinect, capturing 3D data at a rate of 30 Hz. The Azure Kinect SDK was employed to extract body landmarks from the acquired 3D data. Fig. 4 shows the landmarks detected by Azure Kinect SDK and the reflective markers from Vicon®. In this study, the lower and upper body were analyzed, except for the upper limbs. Upper limbs were excluded as the primary focus of gait analysis is often on the actions taken by the lower limbs [22].

A procedure was established for the calculation of joint angles from the Azure Kinect data in a similar way as the Vicon® system does following the Plug-in-Gait model [23]. Using the 3D coordinates of the landmarks captured from the Azure

Kinect, the definition of the coordinate systems of the body segments were first defined consistent with the International Society of Biomechanics recommendations (ISB)[24]. Three local coordinate systems were located in the joints: $R1 = {}^{w}F_{Knee}$, $R2 = {}^{w}F_{Pelvis}$, $R3 = {}^{w}F_{Trunk}$, and joint angles were calculated as follows:

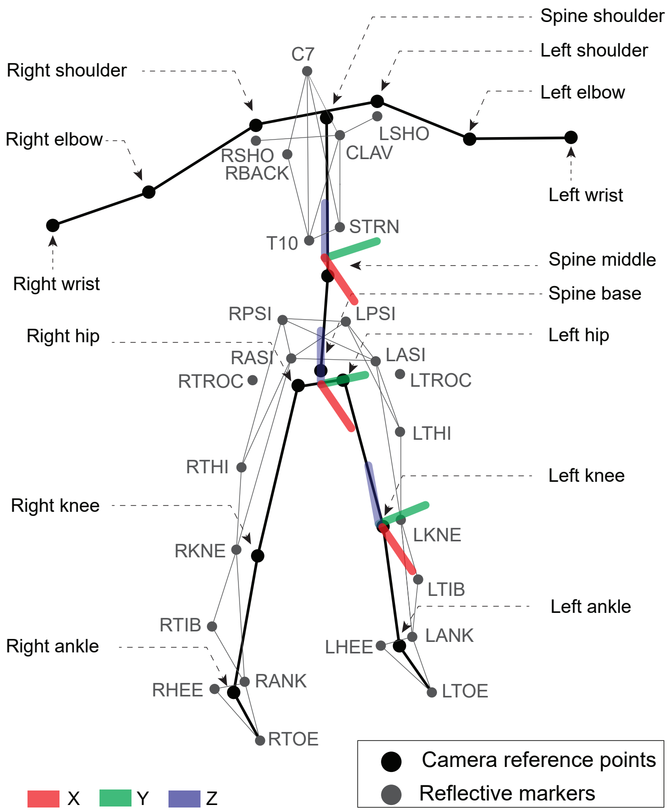

FIGURE 4 Skeleton model used by the mobile robot built from Vicon® markers.

- The hip joint angles were the Euler rotation angles between the pelvic and knee coordinate systems, i.e. the relative rotation $Eyxz1$, where $Eyxz1 = R1 * transpose(R2)$.
- The pelvic angles were the Euler rotation angles between the world and pelvic coordinate frames.This corresponds to the absolute rotation of $R2$.
- The Euler rotation angles between the world coordinate and the trunk coordinate frames were used to determine the trunk angles. This corresponds to the absolute rotation of $R3$.
- The spatial angle between the two vectors crossed at the knee joint center was considered as the knee joint angle.

2.3 | Performance Evaluation

Ten participants were recruited, 4 males and 6 females (31±4 years, 172±7 cm, 66±12 kg). The experiments were developed at the Laboratory of Movement Analysis, Ergonomics and Motor Control (LAMBECOM) of the Rey Juan Carlos University (URJC). All experiments were carried out according to the Helsinki Declaration as a response to concerns regarding research on patient populations.

2.3.1 | Experimental Protocol

Participants performed two tests on the same day, preceded by careful placement and calibration of markers on each participant. The first test involved a walking assessment in the laboratory, followed by a second walking test conducted in the corridors. In both cases, participants had the freedom to self-select their walking speed based on their personal preference. Detailed explanations of each experiment are provided below:

- **Laboratory walking test:** The walking path had 4 effective meters of Vicon® capture, on a walking platform of 8 meters in total. The participant walked in a straight line while the robot moved in front maintaining a distance of 3 meters from the person. Five successive trials were collected per person. Fig. 5 shows this experimental environment.
- **Corridor walking test:** The walking path was about 32 meters, mostly straight path. This path included two curves, the first was a blind curve at 20 meters, and the second, was an open curve, at 27 meters. At the beginning, the participant was explained the path to follow and was asked to walk without considering the robot moving in front and at a preferred walking speed. The robot moved following the predefined path and kept a distance of 3 meters from the participant. Two trials per participant were collected. Fig. 6 shows the experimental trajectory and environment for experiments in corridors.

2.3.2 | Marker-based reference System

A Vicon® Nexus 3D photogrammetric system was used as the reference of measurement. Gait kinematics was exported directly from the Nexus software. The markers were set according to the Vicon® Plug-in Gait model. It included 23 reflective markers and no upper extremities were marked. The toes were marked but were not used during the comparison with the Azure Kinect. The Vicon® sampling rate was 100 Hz.

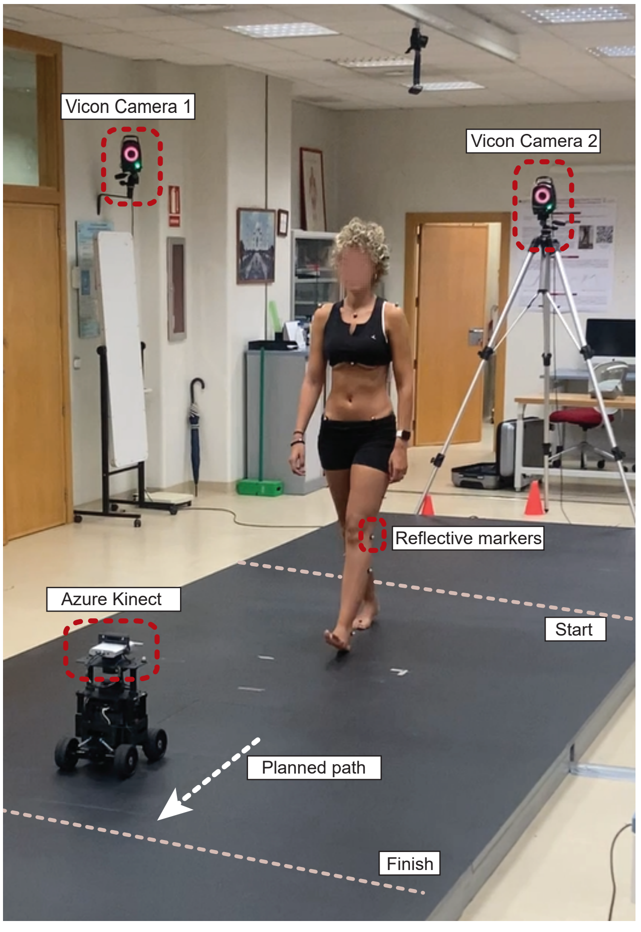

FIGURE 5 Laboratory walking test environment.

2.3.3 | Synchronization and data analysis

The Azure Kinect and the Vicon® system started recording data at different times and through different input streams. The timestamp of the first gait cycle was used to synchronize the data. This event represented the onset of the recording. The end of the recording was imposed by the trial of a shorter duration. The data from both systems was cut between these limits. Due to the difference in sampling frequencies, the Vicon® time series were linearly interpolated using the timestamps of the Azure Kinect data. This process ensured the same query points at the same timestamp. In order to minimize any fluctuation, a low pass filter with a cut-off frequency of 4 Hz was applied to the Azure Kinect data.

Once signals were synchronized and interpolated to the same timestamps, an inverse kinematic process was applied for joint angles calculation as explained in subsection 2.2. Then, relative forward progression of ankle joint centers during walking was used for gait event detection and to split gait cycles in both systems, as suggested by [25]. The relative forward progression of ankles is a characteristic sinusoidal curve in which the valleys correspond to the heel strike event, and the peaks fit with the toe-off event [26]. Following this way to detect gait events, a total of 8 kinematic signals and 22 descriptors per gait cycle were compared. This set of gait descriptors was derived from recommendations by Molina and Carratalá [27] and calculated according to established definitions [28,29].

To calculate the accuracy of the system, the error and correlation of the kinematic signals were measured between systems. In addition, the Intraclass Correlation Coefficient (ICC) 1-1, also known as the one-way random single measures ICC, was employed to assess the absolute agreement and reliability of gait data obtained independently from both the Azure Kinect and Vicon systems. By independently calculating ICC values for the Azure Kinect and Vicon datasets, our aim is to quantify the reliability of each system in capturing consistent gait patterns during multiple sessions (or trials). Higher ICC 1-1 values would indicate greater reliability, signifying strong consistency and reproducibility of measurements within each system. The ICC 1-1 was computed by aggregating all normalized (0-100%) gait cycles collected from each participant and subsequently calculating the average ICC across all participants.

For gait descriptors, in addition to the error calculation, Generalized Estimating Equations (GEE) were used to prove statistical differences with gait descriptors reported by Vicon®. GEE is a statistical methodology used to analyze data with correlated or clustered observations. It is particularly useful when dealing with longitudinal or clustered data, where repeated measurements are taken on the same participants or groups over time. In this study, there are repeated measurements corresponding to each of the sequences performed by the participants. Even, in our case, each participant may contribute more or less gait cycles to the data set, depending on several factors, e.g. the walking speed. GEE is prepared to deal with these types of data sets. GEE was also selected because it can be used even if there is an offset between the signals, which may be a common case when comparing the Vicon® model with other gait models. Stride number was defined as a within-subject factor during the statistical analysis, and the 22 descriptors of gait were defined as separate dependent variables. Correcting for multiple comparisons is a common practice in statistical analysis to reduce the likelihood of obtaining false positive results when conducting multiple hypothesis tests. One commonly used method is the Bonferroni correction, which involves dividing the desired significance level by the number of comparisons being made. Following this method, the significance level was set to $p \leq 0.05/22 = 0.002$ to correct for multiple testing.

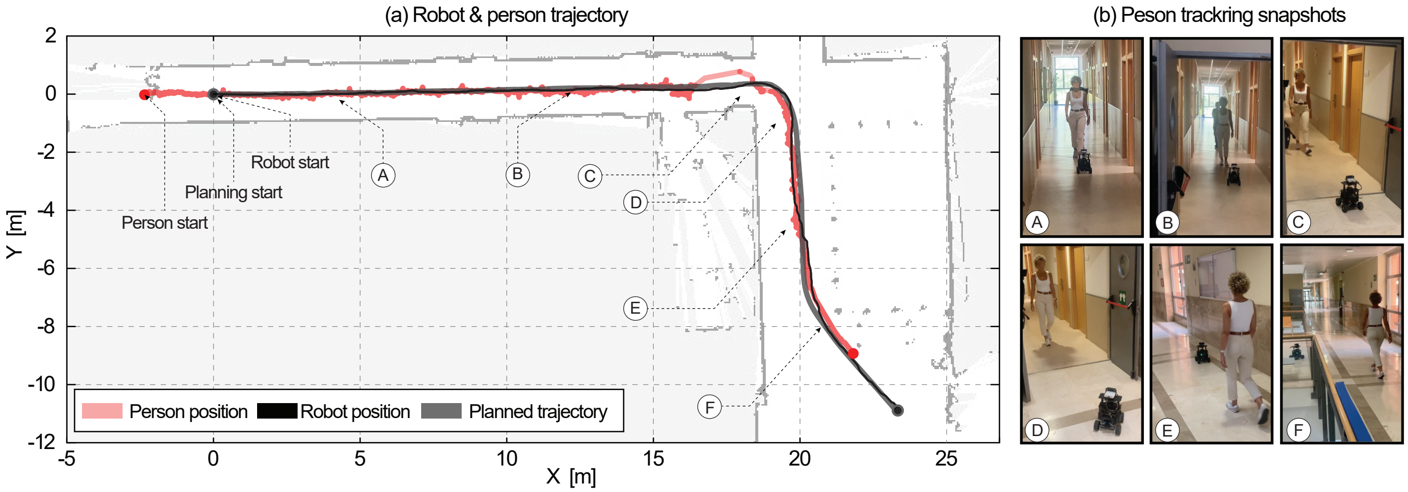

FIGURE 6 The trajectory described in corridor experiments and some snapshots taken in the real environment of the experiment.

3 | RESULTS

The verification of the reliability, validity, and accuracy of the Azure Kinect sensor is important for gait analysis to ensure accurate depth measurement, reliable joint tracking, high-quality motion capture, meaningful comparisons and informed clinical decision-making. Previous studies have already analyzed the accuracy of the Azure Kinect in static conditions of the sensor and from different perspectives [14]. This paper analyzes the accuracy of Azure Kinect for gait analysis in a robot-mounted camera scenario. In a robot-mounted camera scenario, the movement of the robot itself can introduce additional complexities. The robot's motion may affect the camera's stability, introduce vibrations, or alter the perspective and distance to the subject. Validating the impact of the robot's motion on the sensor's performance is important for understanding and accounting for any potential distortions or biases in the gait analysis results.

Table 1 presents the Intraclass Correlation Coefficient (ICC) 1-1 results, accompanied by a 95% confidence interval, illustrating the reliability of gait signals. This statistical measure provides insights into the consistency within each participant across different trials. Complementing the assessment of reliability, the table also showcases the validity outcomes, including Root Mean Square Error (RMSE) and Pearson correlation (r), derived from the comparison of Vicon® and Azure Kinect signals during in-lab experiments.

Notably, knee flex./ext. (ICC-0.95), hip flex./ext. (ICC-0.96), pelvis rotation (ICC-0.88), and inter-ankle distance (ICC-0.98) demonstrated excellent reliability with high confidence. Similarly, hip add./abd. showed good reliability (ICC-0.79), while trunk rotation exhibited moderate reliability (ICC-0.72). In contrast, both trunk tilt (ICC-0.24) and pelvis tilt (ICC-0.41) consistently displayed lower reliability. Surprisingly this was observed for both the Vicon and the Azure systems. The lower ICC values in these specific signals suggest challenges in achieving agreement between the two systems for these particular kinematic measurements. Upon closer examination, it is crucial to acknowledge that trunk tilt and pelvis tilt signals may be more susceptible to variations in marker placement or subtle movements during gait. This sensitivity could contribute to the observed discrepancies, highlighting the intricate nature of capturing precise data for these specific signals.

Regarding the validity outcomes, the error of the Azure Kinect when assessing the knee flex./ext. signal is high, however, the correlation for this signal is strong (12.68°, r=0.97). Hip flex./ext. has a slightly lower error and also a great correlation (5.54°, r=0.96). Hip movement in the frontal plane looks promising (considering that it is usually poorly detected by Azure Kinect sensor) and appears with a moderate correlation (3.45°, r=0.73). Trunk rotation, pelvis rotation, and pelvis tilt, also appear with moderate accuracy and correlation. Other signals such as the inter-ankle distance appear with a low error and a high correlation (0.06 m, r=0.99). Trunk tilt shows a high error and a poor correlation (7.23°, r=0.12). However, when looking at the corresponding subfigure for trunk tilt in Fig. 7, it appears to be caused by the presence of a time delay between signals. This delay could be attributed to a difference between biomechanical models rather than to sensor inaccuracies.

In gait analysis, it is important to analyze not only joint kinematic signals but also gait descriptors. Both types of analysis provide valuable information for understanding and evaluating an individual's gait pattern and can serve different purposes in research, clinical, or performance settings. Table 2 shows the accuracy of the 22 gait descriptors. This table also shows the statistical comparison between systems, presenting non-significant (ns, $p>0.05/22$), significant (*, $p\leq0.05/22$), highly significant

TABLE 1 Intrasession ICC 1-1 values for in-lab data with a 95% Confidence Interval (CI), alongside results from a comparative analysis between systems using Root Mean Square Error (RMSE) and Pearson Correlation (r).

	ICC(CI 95%)		RMSE	r
	Vicon	Azure	(mean±SD)	(mean±SD)
Knee flex./ext. (°)	0.95 (0.92-0.96)	0.95 (0.93-0.96)	12.68±5.12	0.97±0.02
Hip flex./ext. (°)	0.95 (0.93-0.96)	0.96 (0.94-0.97)	5.54±2.43	0.96±0.02
Trunk tilt (°)	0.38 (0.22-0.39)	0.24 (0.15-0.32)	7.23±3.88	0.12±0.35
Pelvis tilt (°)	0.41 (0.25-0.43)	0.41 (0.28-0.43)	4.33±2.08	0.64±0.28
Hip add./abd. (°)	0.85 (0.80-0.86)	0.79 (0.70-0.82)	3.45±1.15	0.73±0.29
Trunk rotation (°)	0.78 (0.70-0.80)	0.72 (0.63-0.75)	5.95±3.39	0.57±0.32
Pelvis rotation (°)	0.59 (0.46-0.61)	0.88 (0.82-0.89)	6.71±3.01	0.65±0.26
Inter Ankle-distance (m)	0.98 (0.98-0.99)	0.98 (0.97-0.99)	0.06±0.02	0.99±0.01

TABLE 2 Mean values and standard deviations (SD) of the main descriptors of gait reported by Vicon® and Azure Kinect. RMSE of the results is shown. The far right column shows the statistical comparison between systems, presenting non-significant (ns, p>0.05/22), significant (*, p≤0.05/22), highly significant (**, p≤0.01/22), and very highly significant (***, p≤0.001/22) differences.

DESCRIPTOR OF GAIT	Vicon(mean±SD)	Azure(mean±SD)	RMSE(mean±SD)	p-value	p-significance
SPATIOTEMPORAL					
left stride time (*s*)	1.10±0.08	1.10±0.08	0.02±0.02	0.6950	ns
left stride length (*m*)	1.15±0.11	1.06±0.12	0.10±0.04	0.0000	***
left step time (*s*)	0.55±0.04	0.54±0.05	0.03±0.02	0.0690	ns
left cadence (*steps/min*)	110.1±8.24	112.31±9.51	5.62±4.18	0.0430	ns
percentage of foot stance (%)	49.98±1.52	50.75±2.71	2.47±1.80	0.0130	ns
percentage of foot swing (%)	50.02±1.52	49.25±2.71	2.47±1.80	0.0130	ns
KINEMATIC					
trunk max. tilt (°)	-2.78±4.32	3.91±3.11	8.54±4.95	0.5720	ns
trunk min. tilt (°)	-6.95±4.88	-1.66±2.34	7.10±4.24	0.0003	**
pelvis max. tilt (°)	7.92±3.09	6.83±3.9	4.2±2.10	0.4820	ns
pelvis min. tilt (°)	4.81±3.09	3.13±3.74	4.36±1.89	0.2960	ns
hip max. adduction (°)	8.35±2.67	3.96±1.93	4.67±1.60	0.0000	***
hip min. abduction (°)	-4.83±3.94	-3.55±2.55	2.71±1.17	0.1640	ns
pelvis max. rotation (°)	5.22±3.48	13.43±3.76	10.23±5.99	0.0010	*
pelvis min. rotation (°)	-4.21±2.26	-5.82±6.22	6.38±2.54	0.4920	ns
hip max. extension during stance (°)	-12.79±5.37	-12.63±4.12	3.64±2.62	0.7860	ns
hip max. flexion during swing (°)	26.6±5.03	22.76±4.47	5.56±3.22	0.0005	*
hip max. flexion during stance (°)	24.02±5.3	18.23±4.24	7.38±3.87	0.0000	***
knee initial contact position (°)	0.80±3.56	6.63±3.37	7.93±5.21	0.0012	*
knee position at toe-off (°)	7.95±5.08	20.36±5.29	14.33±7.23	0.0000	***
knee max. flexion in load response (°)	7.69±4.45	14.87±4.21	8.73±4.78	0.0001	**
knee max. flexion during swing (°)	48.15±10.29	63.04±4.57	18.26±10.04	0.0005	*
knee max. extension before heel strike (°)	0.27±3.33	6.67±3.23	8.07±4.96	0.0001	**

(**, p≤0.01/22), and very highly significant (***, p≤0.001/22) differences of Azure Kinect with reference to Vicon®.

Among the spatiotemporal parameters, left stride time, left step time, left cadence, percentage of foot stance, and percentage of foot swing show no significant differences. In the kinematic parameters, maximum trunk tilt, maximum and minimum pelvic tilt, minimum pelvic rotation, minimum hip abduction, and maximum hip extension also show no significant differences. Pelvis maximum rotation, hip maximum flexion, knee position at initial contact, and knee maximum flexion present only a significant difference. The rest of the descriptors present a highly significant or very highly significant difference.

3.1 | Comparison of in-lab and in-corridor gait patterns

Gait analysis in controlled lab settings involves using specialized equipment like motion capture systems, force plates, or treadmills. While this setup offers advantages such as precise measurements, a controlled setting, and reproducible conditions, it does not always replicate real-life scenarios accurately, potentially resulting in altered gait patterns. Participants might adopt a more cautious or unnatural gait due to equipment presence or self-awareness. This comparison delves into gait patterns between lab and corridor walking tests, aiming to uncover how environments impact gait characteristics.

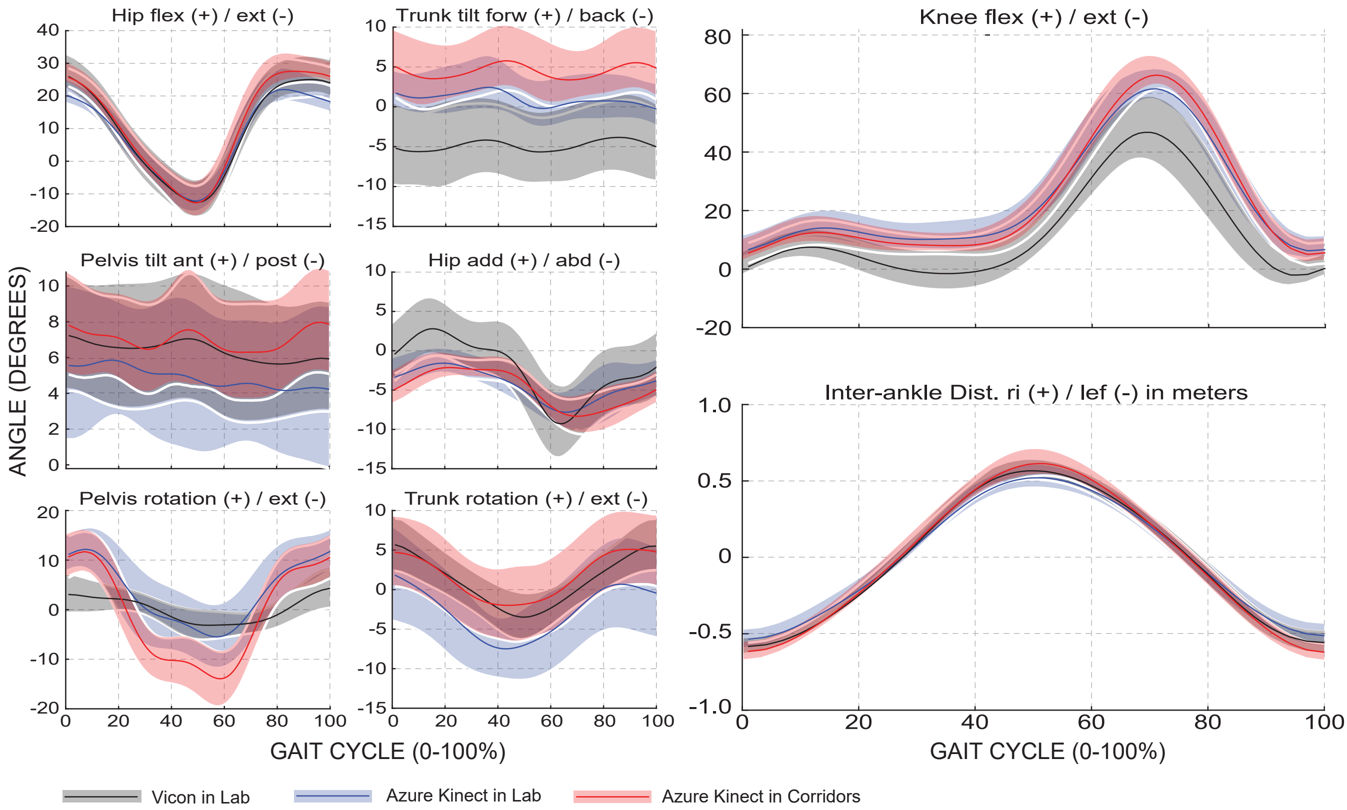

FIGURE 7 Mean and standard deviation of gait signals obtained from 10 participants. The gray and blue graphs show the results reported by Vicon® and Azure Kinect for the walking tests in the laboratory. The red color graph shows the results reported by the Azure Kinect for the walking tests in corridors.

The system's initial validation focused solely on straight-line locomotion in the laboratory setting. Acknowledging this limitation, we took a cautious approach when analyzing data from corridor walking. Specifically, we excluded gait data from curved sections (C to D and E to F in Fig. 6) to ensure statistical integrity. This exclusion aimed to maintain precise comparisons between walking dynamics in straight lines in lab and in corridor environments, avoiding potential confounding factors posed by non-validated curved trajectories. Additionally, our statistical comparison was concentrated on the 11 gait descriptors that exhibited no significant differences in lab tests compared to the Vicon® system.

In Fig.7, the comparison results display the mean and standard deviation of kinematic signals captured in both environments, for ease of understanding potential differences, and they are summarized in Table 3. Using a Bonferroni correction, a significance level of $p \leq 0.05/11 = 0.004$ was set for multiple testing.

Among the 11 gait descriptors, maximum pelvis tilt and minimum pelvis rotation exhibit highly significant differences between laboratory and corridor walking. This suggests that the controlled environment and restricted mobility may diminish the need for significant pelvic tilt movements during gait. Specifically, participants showed significantly lower maximum pelvis tilt (6.83°in-lab vs. 9.39°in-corridors) and lower minimum pelvis tilt (3.13°in-lab vs. 4.78°in-corridors), indicating a less dynamic and adaptive gait in the lab.

Additionally, minimum pelvis rotation, an indicator of external pelvis rotation, also shows notable disparities in the lab setting. Participants exhibited significantly reduced minimum pelvic rotation (-5.82°) compared to corridor walking (-14.61°), potentially due to the absence of terrain adaptation requirements in the controlled lab environment.

Finally, the specific characteristics of the laboratory and corridor conditions, such as their dimensions, surface properties, among others, may also impact stride time. The results show that the stride time is significantly longer when walking in laboratories (1.10s) than when walking in corridors (1.05s). Although the rest of the parameters show no statistically significant difference, their higher values demonstrate a more dynamic gait in the corridors and a more cautious or constrained gait pattern during walking in the laboratory.

TABLE 3 Comparison of in-lab and in-corridor gait patterns. The far right column shows the statistical comparison between conditions, presenting non-significant (ns, p>0.05/11), significant (*, p≤0.05/11), highly significant (**, p≤0.01/11), and very highly significant (***, p≤0.001/11) differences.

DESCRIPTOR OF GAIT	in-Lab (mean±SD)	in-Corridor (mean±SD)	p-value	p-significance
SPATIOTEMPORAL				
left stride time (*s*)	1.10±0.08	1.06±0.08	0.0017	*
left step time (*s*)	0.54±0.05	0.53±0.05	0.1354	ns
left cadence (*steps/min*)	112.31±9.51	115.20±12.28	0.1175	ns
percentage of foot stance (%)	50.75±2.71	51.06±2.38	0.4162	ns
percentage of foot swing (%)	49.25±2.71	48.94±2.38	0.4162	ns
KINEMATIC				
trunk max. tilt (°)	3.91±3.11	7.06±3.62	0.4061	ns
pelvis max. tilt (°)	6.83±3.90	9.44±2.42	0.0000	***
pelvis min. tilt (°)	3.13±3.74	4.83±2.95	0.0005	**
hip min. abduction (°)	-3.55±2.55	-4.01±2.51	0.2442	ns
pelvis min. rotation (°)	-5.82±6.22	-14.36±4.95	0.0000	***
hip max. extension during stance (°)	-12.63±4.12	-13.04±5.08	0.5874	ns

4 | DISCUSSION

Exploring the results obtained with Azure Kinect in comparison with 2D video-based pose estimation methods offers interesting insights into the field of gait analysis technologies. In a comparative analysis, Washabaugh et al.[11] evaluated four open-source pose estimation methods, including OpenPose and Tensorflow MoveNet Thunder. These methods showcased notable accuracy, particularly in hip kinematics, with OpenPose and Tensorflow MoveNet Thunder averaging 3.7 ± 1.3 and 4.6 ± 1.8 degrees, respectively. Conversely, the Azure Kinect sensor mounted on a mobile robot exhibited a slightly higher error of 5.54±2.43 degrees, considering experimental nuances such as dynamic camera movement. Despite these experimental conditions, the results obtained for the Azure Kinect are better than those reported for Tensorflow MoveNet Lightning and DeepLabCut pose estimation methods (5.9±3.6 degrees and 6.8±1.6 degrees, respectively). Further comparisons revealed that Azure Kinect exhibited higher error in knee kinematics (12.68±5.12 degrees) compared to OpenPose (5.1±2.5 degrees). Tensorflow MoveNet Thunder exhibited greater accuracy in measuring the step time of the left leg (0.02±0.02 seconds) compared to OpenPose (0.03± 0.02 seconds) and DeepLabCut (0.04± 0.04 seconds). In our study, the Azure Kinect sensor demonstrated a similar accuracy of 0.02±0.02 seconds. In other studies, Menychtas et al.[30] compared OpenPose and Mediapipe with Vicon® and Kinovea, favoring OpenPose despite higher computational costs. Ota et al.[31] evaluated OpenPose's accuracy, reporting 2 degrees of error for knee flexion and around 7 degrees for knee extension during fast walking. Notably, while OpenPose excelled in accuracy, its lower frame rate (22 Hz) might pose challenges in gait analysis compared to Azure Kinect's 30 Hz capability.

In the study presented by Trend et al.[13], Azure Kinect and a 12-camera Vicon® system were compared for overground walking. The study was conducted on a group of healthy participants with the sensor static and placed in front. The study reported an error of 0.03 m for stride length (vs. 0.1 m in our study) and 0.01s for stride time (vs. 0.02s in our study). The results are close to those obtained in our study even though the camera was static and in our study it was mounted on a mobile robot.

When compared to other setups using Azure Kinect, in the study of Ling et al.[14] an error of 4.0±1.2 degrees was reported for hip adduction/abduction with a very high significant difference for maximum and minimum excursions. This is close to the error reported in our study, where an error of 4.67±1.60 degrees was found for maximal adduction and 2.71±1.17 degrees for minimal abduction. However, in our study, only highly significant differences were observed for maximal adduction and nonsignificant for minimal abduction. Ling et al. reported lower excursions in the frontal plane (maximum adduction of 1.3 degrees and minimum abduction of -1.9 degrees), whereas our study reported higher excursions (maximum adduction of 3.96°and minimum abduction of -3.55°). This could be explained because Ling et al. tracked gait kinematic patterns during treadmill walking, which typically provides a more stable and controlled environment compared to overground walking, which may result in reduced lateral movement at the hip joint.

Ling et al. also reported an error of 9.6±4.7 degrees for hip motion in the sagittal plane, with a significant difference for maximum flexion and not for maximum extension, just as obtained in our study. However, the overall error reported in our study (5.54±2.43 degrees) is lower than that reported by Ling et al. When analyzing the maximum flexion and extension values, a higher flexion excursion (22.76°in our study vs. 17.3°for Ling et al.) and lower extension (-12.63°in our study vs. -16.8°for Ling et al.) were obtained. This may be explained as during overground walking compared to treadmill walking, hip flexion may be greater, while hip extension may be less[32]. This difference may be attributed to several factors, including the need to propel forward during overground gait and the mechanical properties of the treadmill. Finally, Ling et al. reported an overall error in knee flexion of 16.1±5.4 degrees, while we reported 12.68±5.12 degrees with a significant difference.

In the work of Yunru et al.[33], five healthy participants were evaluated during an overground gait. The accuracy of different lower extremity gait kinematic parameters was determined using a dual Azure Kinect compared to Vicon®. A dual Azure Kinect setup (one in front of the other, 4 m distance from each other) was applied to avoid occlusion between body segments during gait. The errors obtained in comparison with those presented in our study were as follows: 15.1°for hip flex./ext. (vs. 5.54°for ours), 7.2°for hip add./abd. (vs. 3.45°for ours), and 11.9°for knee knee flex./ext. (12.68°for ours). Although the author does not describe the orientation of the cameras, an image is shown where the cameras have too much tilt angle, aiming towards the ground. The high error observed in the hip flex./ext. and hip add./abd. compared to the current study, may be related to a poor capture of the pelvis segment due to a misaligned orientation of the cameras. In the current study, the camera is supported on a structure that keeps it horizontal, which allows a better visualization of the participant.

As can be appreciated, the overall error of our robot-mounted camera configuration is close to that reported by Ling et al. which uses a static sensor placed in front of the participant and a treadmill. Compared to Yunru et al., the results presented in our study are better probably due to an improved orientation of the sensor. These comparisons validate the configuration proposed in the current study and ensure the absence of influence of camera motion during gait assessment.

Investigating the differences between gait in-lab and in-corridor is important for a comprehensive understanding of human locomotion. This study has also attempted to use the proposed configuration for comparison of in-lab and in-corridor gait patterns based solely on the 11 gait descriptors that show no significant differences compared to Vicon®. Several studies have previously investigated the effect of the experimental environment on gait patterns and have reported the presence of differences. Susan E. et al.[34], assessed the effect of the environment on gait parameters in a community of ambulant stroke survivors. Analysis of variance showed a significant main effect of environmental conditions (p=0.046). The main difference found was a decrease in walking speed of 8.5m/min for an outdoor environment compared with a clinic environment. In that study, step frequency and step length were not significantly altered as a result of walking in different environments. Considering the decrease in gait speed related to longer stride time, our study showed an opposite result, with shorter stride time in the external environment, with significant differences. However, it is important to note that health conditions can influence walking speed. In general stroke survivors may exhibit a lower walking speed in external environments because they commonly experience balance impairments and altered coordination, which can affect their ability to navigate in real-world environments[35].

Besharat et al.[36], also reported differences when evaluating Pakinson's disease patients in virtual doorway and hallway environments compared to laboratory environments. Compared to the physical laboratory, reduced joint excursions of the knee and hip were found when walking in virtual doorway and hallway environments compared to the physical laboratory. Also, peak swing phase toe clearance, arm swing, and inclination angle were reduced, and walking was slower, with shorter and wider steps. This is normal since the perception of space might contribute to the Freezing of gait in Parkinson's disease[37], which results in walking with reduced speed and stride length.

Scanlon J.M.[38], conducted a study to compare gait performance between different environments for a healthy patient group more similar to that involved in our study. Spatiotemporal and kinematic gait characteristics were obtained from 19 young adults during various gait conditions, both inside a laboratory environment and outdoors on a 10.8-meter-long concrete sidewalk area. Experiments were conducted using a Vicon® system and an Xsens inertial measurement unit system. When comparing walking at a self-selected speed, walking speed was 1.7% slower in-lab (approx. 1.35m in-lab vs. 1.38 outdoors, p<0.001), and cadence was 2.0% slower in-lab (approx. 108 steps/min. in-lab vs. 110 steps/min outdoors, p<0.001). Stride length was also lower in-lab, but showed no significant difference.

Finally, in our study, significant differences were found for pelvic tilt and rotation, with decreased movements for walking in-lab. As mentioned before, the controlled environment and absence of freedom to walk during in-lab tests may reduce the need for significant pelvic tilting movements. In contrast, when walking in corridors, the increased pelvic tilt movement could be related to the higher walking speed and cadence reported in this study. This is because as walking speed increases, pelvic tilt tends to increase as a compensatory mechanism to maintain balance and stability.

Recognizing the limitations of the present study, it is important to emphasize that the participant pool consists mainly of healthy individuals. This limitation limits the generalizability of the results to populations with specific pathologies. In future work, this limitation is planned to be addressed by expanding the study to include individuals with gait impairments, such as those with Multiple Sclerosis (MS). In addition, the countless contributions of the community to the gait analysis using the Azure Kinect sensor encourage the realization of this work, however, the manufacturer stopped the production of these sensors becoming a great issue for further studies. In this matter, we are studying how to migrate our approach to a novel similar sensor like the ORBBEC Femto Mega[39] that has experienced important growth in the market.

5 | CONCLUSIONS

This study presents a markerless gait analysis system that uses an Azure Kinect sensor mounted on a mobile robot. This configuration is proposed and validated as a potential solution for gait analysis in corridors. The overall error obtained for the robot-mounted camera configuration closely aligns with the values reported in the literature, where static sensors and treadmills are commonly used for gait assessment. This validation confirms the effectiveness of the proposed configuration and ensures the absence of any influence from camera motion.

Most of the kinematic signals demonstrate good to moderate accuracy and correlation. Particularly, the inter-ankle distance, which is utilized to describe most of the spatiotemporal parameters, exhibits high correlation and accuracy when compared to the Vicon® system. However, the results for the trunk tilt signal display poor performance, attributed to the observed time delay between signals likely caused by differences in biomechanical models. This work analyses a total of 22 gait parameters, and out of these, 11 parameters show no significant differences when compared to the Vicon® system.

Based on these 11 parameters, this study investigates the differences in gait patterns when individuals walk in the laboratory compared to corridors. Gait patterns exhibit variations depending on the environment. The pelvis segment demonstrates the most pronounced differences, with reduced significant movements observed when participants are evaluated in the laboratory. Additionally, stride time decreases when assessed in the laboratory. Although the remaining parameters do not exhibit statistically significant differences, their higher values distinctly highlight a more dynamic gait in corridors and a more cautious or constrained gait pattern in the laboratory.

The findings of this study underscore the potential of Azure Kinect for gait analysis in a robot-mounted camera scenario, encouraging the assessment of outdoor gait patterns. These patterns have been demonstrated to differ from those evaluated in the laboratory, emphasizing the importance of considering real-world environments in gait analysis. Finally, in further works, a deeper analysis concerning the extraction of the parameters from the skeleton will be included.

AUTHOR CONTRIBUTIONS

All authors contributed equally to this work.

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FINANCIAL DISCLOSURE

None reported.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

PATIENT CONSENT STATEMENT

Informed consent was obtained from all subjects involved in the study.

REFERENCES

1. Sanders RD, Gillig PM. Gait and its assessment in psychiatry.. *Psychiatry (Edgmont (Pa. : Township)).* 2010;7(7):38–43.
2. Herran M.-d.-lA, García-Zapirain B, Méndez-Zorrilla A. Gait analysis methods: An overview of wearable and non-wearable systems, highlighting clinical applications. *Sensors (Switzerland).* 2014;14(2):3362–3394. doi: 10.3390/s140203362
3. Viswakumar A, Rajagopalan V, Ray T, Gottipati P, Parimi C. Development of a Robust, Simple, and Affordable Human Gait Analysis System Using Bottom-Up Pose Estimation With a Smartphone Camera. *Frontiers in Physiology.* 2022;12. doi: 10.3389/fphys.2021.784865
4. Wade L, Needham L, McGuigan P, Bilzon J. Applications and limitations of current markerless motion capture methods for clinical gait biomechanics.. *PeerJ.* 2022;10:e12995. doi: 10.7717/peerj.12995
5. Cao Z, Hidalgo G, Simon T, Wei S, Sheikh Y. OpenPose: Realtime Multi-Person 2D Pose Estimation Using Part Affinity Fields. *IEEE Transactions on Pattern Analysis & Machine Intelligence.* 2021;43(01):172–186. doi: 10.1109/TPAMI.2019.2929257
6. Abadi M, Barham P, Chen J, et al. TensorFlow: A System for Large-Scale Machine Learning. In: OSDI'16. USENIX Association 2016; USA:265–283.
7. Maji D, Nagori S, Mathew M, Poddar D. YOLO-Pose: Enhancing YOLO for Multi Person Pose Estimation Using Object Keypoint Similarity Loss. In: IEEE 2022:2636–2645
8. Mathis A, Mamidanna P, Cury KM, et al. DeepLabCut: markerless pose estimation of user-defined body parts with deep learning. *Nature Neuroscience.* 2018;21(9):1281–1289. doi: 10.1038/s41593-018-0209-y
9. Gupta A, Shrestha PL, Thapa B, Silwal R, Shrestha R. Knee Flexion/Extension Angle Measurement for Gait Analysis Using Machine Learning Solution "MediaPipe Pose" and Its Comparison with Kinovea®. *IOP Conference Series: Materials Science and Engineering.* 2023;1279(1):12004. doi: 10.1088/1757-899X/1279/1/012004
10. Bazarevsky V, Grishchenko I, Raveendran K, Zhu T, Zhang F, Grundmann M. BlazePose: On-device Real-time Body Pose tracking. *arXiv.* 2020.
11. Washabaugh EP, Shanmugam TA, Ranganathan R, Krishnan C. Comparing the accuracy of open-source pose estimation methods for measuring gait kinematics. *Gait & Posture.* 2022;97:188–195. doi: https://doi.org/10.1016/j.gaitpost.2022.08.008
12. Nor Adnan NM, Ab Patar MNA, Lee H, Yamamoto SI, Jong-Young L, Mahmud J. Biomechanical analysis using Kinovea for sports application. *IOP Conference Series: Materials Science and Engineering.* 2018;342(1):12097. doi: 10.1088/1757-899X/342/1/012097
13. Guess TM, Bliss R, Hall JB, Kiselica AM. Comparison of Azure Kinect overground gait spatiotemporal parameters to marker based

optical motion capture. *Gait & Posture.* 2022;96:130–136. doi: 10.1016/j.gaitpost.2022.05.021
14. Yeung LF, Yang Z, Cheng KCC, Du D, Tong RKY. Effects of camera viewing angles on tracking kinematic gait patterns using Azure Kinect, Kinect v2 and Orbbec Astra Pro v2. *Gait & Posture.* 2021;87:19–26. doi: https://doi.org/10.1016/j.gaitpost.2021.04.005
15. Ma Y, Sheng B, Hart R, Zhang Y. The validity of a dual Azure Kinect-based motion capture system for gait analysis: a preliminary study. In: 2020:1201–1206.
16. Pfister A, West AM, Bronner S, Noah JA. Comparative abilities of Microsoft Kinect and Vicon 3D motion capture for gait analysis. *Journal of Medical Engineering & Technology.* 2014;38(5):274–280.
17. Scheidig A, Jaeschke B, Schuetz B, et al. May I Keep an Eye on Your Training? Gait Assessment Assisted by a Mobile Robot*. In: 2019:701–708
18. Terven JR, Córdova-Esparza DM. KinZ an Azure Kinect toolkit for Python and Matlab. *Science of Computer Programming.* 2021;211:102702. doi: 10.1016/j.scico.2021.102702
19. Rösmann C, Feiten W, Wösch T, Hoffmann F, Bertram T. Efficient trajectory optimization using a sparse model. In: 2013:138–143
20. Guffanti D, Brunete A, Hernando M. Development and validation of a ROS-based mobile robotic platform for human gait analysis applications. *Robotics and Autonomous Systems.* 2021;145:103869. doi: 10.1016/j.robot.2021.103869
21. Guffanti D, Brunete A, Hernando M, Rueda J, Navarro E. ROBOGait: A Mobile Robotic Platform for Human Gait Analysis in Clinical Environments. *Sensors.* 2021;21(20):6786. doi: 10.3390/s21206786
22. Sadeghi H, Allard P, Duhaime M. Functional gait asymmetry in able-bodied subjects. *Human Movement Science.* 1997;16(2):243–258. doi: https://doi.org/10.1016/S0167-9457(96)00054-1
23. Baker R, Leboeuf F, Reay J, Sangeux M. The Conventional Gait Model : The Success and Limitations. In: , , , 2017:1–19
24. Wu G, Cavanagh PR. ISB recommendations for standardization in the reporting of kinematic data. *Journal of Biomechanics.* 1995;28(10):1257–1261. doi: 10.1016/0021-9290(95)00017-C
25. Ceccato JC, Sèze dM, Azevedo C, Cazalets JR. Comparison of Trunk Activity during Gait Initiation and Walking in Humans (Trunk Activity in Walking). *PLoS One.* 2009;4(12).
26. Zeni JA, Richards JG, Higginson JS. Two simple methods for determining gait events during treadmill and overground walking using kinematic data. *Gait & Posture.* 2007;27(4):710–714.
27. Francisco M, Carratalá M. *La Marcha Humana: Biomecánica, Evaluación y Patología.* Madrid: Editorial Médica Panamericana, 2020.
28. Beauchet O, Annweiler C, Lecordroch Y, et al. Walking speed-related changes in stride time variability: Effects of decreased speed. *J. Neuroeng. Rehabil..* 2009;6(1):32.
29. Müller B, Ilg W, Giese MA, Ludolph N. Validation of enhanced kinect sensor based motion capturing for gait assessment. *PLoS One.* 2017;12(4):1–18. doi: 10.1371/journal.pone.0175813
30. Menychtas D, Petrou N, Kansizoglou I, et al. Gait analysis comparison between manual marking, 2D pose estimation algorithms, and 3D marker-based system.. *Frontiers in rehabilitation sciences.* 2023;4:1238134. doi: 10.3389/fresc.2023.1238134
31. Ota M, Tateuchi H, Hashiguchi T, Ichihashi N. Verification of validity of gait analysis systems during treadmill walking and running using human pose tracking algorithm. *Gait & Posture.* 2021;85:290–297. doi: https://doi.org/10.1016/j.gaitpost.2021.02.006
32. Yao J, Guo N, Xiao Y, et al. Lower limb joint motion and muscle force in treadmill and over-ground exercise. *BioMedical Engineering OnLine.* 2019;18(1):89. doi: 10.1186/s12938-019-0708-4
33. Ma Y, Mithraratne K, Wilson N, Zhang Y, Wang X. Kinect V2-Based Gait Analysis for Children with Cerebral Palsy: Validity and Reliability of Spatial Margin of Stability and Spatiotemporal Variables.. *Sensors (Basel, Switzerland).* 2021;21(6). doi: 10.3390/s21062104
34. Lord SE, Rochester L, Weatherall M, McPherson KM, McNaughton HK. The Effect of Environment and Task on Gait Parameters After Stroke: A Randomized Comparison of Measurement Conditions. *Archives of Physical Medicine and Rehabilitation.* 2006;87(7):967–973. doi: 10.1016/j.apmr.2006.03.003
35. Middleton A, Braun CH, Lewek MD, Fritz SL. Balance impairment limits ability to increase walking speed in individuals with chronic stroke. *Disability and Rehabilitation.* 2017;39(5):497–502. doi: 10.3109/09638288.2016.1152603
36. Besharat A, Imsdahl SI, Yamagami M, et al. Virtual reality doorway and hallway environments alter gait kinematics in people with Parkinson disease and freezing. *Gait & Posture.* 2022;92:442–448. doi: https://doi.org/10.1016/j.gaitpost.2021.12.013
37. Almeida QJ, Lebold CA. Freezing of gait in Parkinson's disease: a perceptual cause for a motor impairment?. *Journal of Neurology, Neurosurgery & Psychiatry.* 2010;81(5):513–518. doi: 10.1136/jnnp.2008.160580
38. Scanlon J. *Comparing Gait Between Outdoors and Inside a Laboratory*. PhD thesis. Virginia Polytechnic Institute and State University, Blacksburg, VA; 2014
39. Brief P, Specifications P, Information P, et al. Femto Mega. WebPage; 2023.