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# A Methodology for Assessing the Impact of Error Components in Gait Analysis Using Closed-Loop Testing on a Biomimetic Rig

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**Abstract.** Scientific gait analysis methods aim to offer objective measurements, to assist physicians towards an accurate diagnosis or pre-diagnosis of ailments before they actually manifest through noticeable symptoms. This paper reviews selected gait analysis system technologies, trends, applications and discusses errors and precision in spatial and angular readings. Furthermore, we propose a novel test and calibration method using a biomimetic rig. To illustrate this, we conduct three tests on an optical single-camera gait analysis system based on a mobile android smart-phone with specially developed software.

**Keywords.** gait analysis, biomimetic rig, exoskeleton systems

## 1. Introduction

The multiple applications of human gait analysis can be categorized in eight main fields: health, sports, entertainment, education, ergonomics, exoskeletons, robotics and security, with health being the most important. The global ageing tendency and the associated ailments (e.g., Parkinson's and osteoarthritis) amplify motorial problems dramatically. In addition, increased traffic accidents, obesity, mass sporting activities, orthopaedic surgeries, urge for solutions in compensating incorrect gait cycle. Exoskeleton mechanisms for the human limbs can help alleviate such problems. The design procedure of safe exoskeleton mechanisms (including prototyping, programming, debugging, calibrating, testing, foolproofing) necessitates the study of a significant number of gait cycles derived from numerous individuals both patients and healthy volunteers.

Each human being has its own distinctive gait, or, rather, set of gaits, adapting to speed, terrain, carried load, fatigue, etc. Individual gait patterns change due to age, occupation, working conditions, sport activities, hobbies, life style, health issues. Various abnormalities, asymmetries of the gait cycle, or significant deviations from the standards, are indicative of possible underlying pathological conditions that can help doctors focus on specific ailments or conduct prediagnosis [1]. Benchmarking, i.e., comparison with deviation analysis, against a previously executed gait analysis at a

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younger age, or against standard (typical) healthy population values, may reveal heart diseases [2], imminent cardioarrest, Parkinson's, and other syndromes including myopathies [3]. Gait analysis is the systematic study of human locomotion objectively (using instruments to record physical measurements), subjectively (based on the observation of experienced physicians), or semi-subjectively. Numerous protocols cover both objective and semi-subjective gait measuring techniques, by recording and analyzing measurable gait parameters such as: step length, walking speed, swing and stance durations, joint angles, muscles force, left and right asymmetries. For example, Extra Laboratory Gait Assessment Method evaluates gait parameters such as step length, speed and head turning ability while walking, in order to identify risk factors for falls among the elderly at home [4]. Miniaturized sensors and mechatronic devices for gait study can be categorized in three main groups:

- Contact Wearables, including in-shoe and in-sole systems, body sensors such as accelerometers, gyroscopes, magnetometers, extensometers, goniometers, EMG electromyography, EEG encephalography, etc., allow the subject to walk freely in an uncontrolled environment [5]. Combined study of multiple sensor data is a common method [6].
- Contact Non-Wearables, e.g., pressure measuring platforms such as forceplates and walkways with capacitive sensors, piezoelectric, piezoresistive and ultrasonic sensors, can be significantly more precise and accurate than wearables, but also more expensive, typically designed for lab and clinical experiments, constraining motion to a few square meters or less.
- Non Contact, image recording and processing systems with analog or digital cameras, laser range scanners, infrared sensors, active or passive markers, time-of-flight cameras and usual or structured lighting.

In order to identify subtle gait differences, the measurement system should be of known accuracy. Preferably, the error components should be an order of magnitude smaller than the characteristics to be detected. In general, gait measurement errors are induced by instruments, software, physical phenomena, protocols, practitioners, subjects. Numerous papers deal with the precision of gait analysis systems and the validity of the data obtained, aiming at improving overall accuracy in diagnosis.

In the following section (No2), we discuss about error components, accepted limits, and comment on objectives and research questions of the current paper. Additionally an alternative methodology for evaluating gait analysis systems, employing a biomimetic rig, without resulting to Golden standard systems, is proposed in section 3. The use of the rig (subsection 3.2) offers two major benefits, firstly, the exclusion of human volunteers from the experiments, and secondly, the exclusion of human error factors in gait repetition. Illustrated test examples of the methodology are presented in section 4. They can check hypotheses such as "the particular gait analysis system has the required knee angle measurement precision for the diagnosis of that specific ailment". The hypothesis is discussed in last paragraph of section 4. Discussion section (No 5), reviews presented methodology and the contributions of the current paper.

## 2. Related Work

Modern multi-camera systems can offer 3D markers' coordinate accuracies better than 0.03mm. Consequently, other error factors become prevalent in lab setups. The most crucial factor affecting inferred joint coordinates and infusing errors - often beyond the acceptability of the gait analysis community - is the misplacement of markers on the body of the subject. Misplacement (e.g., due to different protocols / practices among physicians, obesity, subject's morphology / wounds / cooperation spirit) may account for an angle error exceeding the $5^o$ acceptance limit which is what a trained eye is likely to differentiate [1]. The study of 10 children with cerebral palsy against 10 aged-matched typical developing children, showed that anterior-posterior misplacement of the lateral epicondyle marker, led to hip internal-external rotation angle offsets of $5.3^o$ per 10mm of displacement [7]. Determination of the ankle's internal-external rotation angle, demonstrated a sensitivity of $4.4^o$ per 10mm offset. Naturally, measurements tend to worsen according to the ratio of the misplacement to leg length: the smaller the length, the bigger the angle error. It was concluded that in order to achieve an error below the limit of $5^o$ on all joints, a physician needs a repeatability precision below 1.2% of the leg length when placing the markers [7].

In some cases, the disparity of angle measurements between labs reached $34^o$ [8]. It can be attributed mainly to different testers and the plurality of marker placement protocols.

Based on the reported experiments conducted in swimming pool, with calm water [9], a two action cameras setup, with extensive calibration and non-linear optical distortion model, yielded reconstruction accuracy of 1.5mm at highres mode 1920x1080p and 2.5mm at lowres 1280x720p. The work volume was 1x4x1.5m and cameras were placed 1m away. Linear camera model increased the error up to 10mm.

A single RGB-D camera (Microsoft Kinect V2, 2.5D color +infrared camera) was used for the gait analysis of 20 subjects [10]. Machine learning algorithms processed the data and achieved a step-length mean absolute error of 42mm (with standard deviation of 42mm) when walking towards the camera, compared against the gold standard Qualisys system with 12 cameras laboratory setup.

Two versions of Kinect (V1 & V2) were compared, against a laboratory motion capture system [11]. Joints coordinate errors ranged from 50 to 100mm and varied according to distance from center of camera.

The $MO^2CA$ single iPhone camera system was compared to the golden standard Qualisys with 8 cameras setup [12]. Although spatial $MO^2CA$ measurements had an error up to 10mm, a non-inferiority statistical test showed that regarding stride length, stride time, stride length variability, stride time variability, $MO^2CA$ was not inferior to multi-camera Qualisys.

According to the DMS method [13], a single camera setup with multiple markers on joints and head could reconstruct 3D coordinates with maximum linear displacement error of 77mm, with averages from 4 to 33 mm. Inferred joint angles maximum error is $38^o$, with averages from 2.4 to $11.6^o$.

In more complex environments, physical phenomena such as water turbulence and air bubbles during swimming [11], or snow spraying in skiing activities [14], can blind optical equipment leaving large gaps of unmeasured track.

Other factors such as subject's speed do induce errors well above standard stance, that in addition to soft tissue/suit artifacts, could result in a total measurement of up to 8.3 +/- 7.1mm, with absolute maximum values being several times higher [14].

Synopsizing, although Golden standard systems, for clinical and lab use, achieve sub-millimeter accuracy, yet, reports from labs with such systems still contain significant measurement errors, mainly due to personnel, protocols and less-than-ideal conditions.

Furthermore, there is increased interest in new low-cost and portable gait analysis systems [15] which are now forming a new market trend. These systems are typically benchmarked with the aid of the golden standard systems [16]. There is also increased interest in new methods that could assess the accuracy of such portable gait systems, at a lower cost, or in a portable manner, especially for systems located in distant areas, away from the ease of reach of Golden systems. Also, another missing ingredient towards the evaluation, is a way to benchmark and calibrate such systems by excluding the human factor noise from the human gait repetition. Such a method is to be presented in the following section.

## 3. Proposed Methodology

In order to assess any gait analysis system, we have it record and analyze the gait of a biomimetic rig. Afterwards, we compare the results against the known properties of the emulated gait and determine the intra-equipment variability. The rig manages to exclude the inherent human intra-subject variability. This section presents examples of open (A,B) and closed-loop testing (C). The scope of the paper is not to assess the particular optical gait analysis system under test, but to demonstrate that induced errors are easily visualized and identified and secondly present the utility of the proposed methodology. Such tests, summarized in figure 1, could be conducted after a gait system's calibration at the initial setup, and periodically later on. They form a procedure that could assess/enhance the manufacturers' calibration and the users' efficiency.

| | Test phases | Test A | Test B | Test C |
|---|---|---|---|---|
| 1 | Select location (plain background, without moving objects) | √ | √ | √ |
| 2 | Setup treadmill (for easy access and good side-view) | | | √ |
| 3 | Fix phone / tablet on tripod / base for a perpendicular side-view | √ | √ | √ |
| 4 | Inspect scene through camera and focus frame on the desired area | √ | √ | √ |
| 5 | Setup lights. Ensure uniform lighting, without shadows/bright spots. | √ | √ | √ |
| 6 | Brief subject (volunteer) on the experiment to be conducted | | | √ |
| 7 | Get subject's written approval / consent | | | √ |
| 8 | Attach markers on human subject | | | √ |
| 9 | Start recording | | | √ |
| 10 | Conduct experiment (stand / walk / jog / run) | | | √ |
| 11 | Stop recording (pause / resume / stop) | | | √ |
| 12 | Extract data from device for further analysis | | | √ |
| 13 | Remove targets from subject | | | √ |
| 14 | Attach markers on rig | √ | √ | √ |
| 15 | Download data to rig | √ | √ | √ |
| 16 | Start recording | √ | √ | √ |
| 17 | Start rig motion / set to desired pose | √ | √ | √ |
| 18 | Stop recording | √ | √ | √ |
| 19 | Extract data from device for further analysis | √ | √ | √ |
| 20 | Remove targets from rig | √ | √ | √ |
| 21 | End session | √ | √ | √ |

**Figure 1.** Work flowchart for Tests A, B and C

It is apparent that not all tests include the same phases. For example, in test A and B there is no need for a human volunteer, so human related phases are omitted.

Test A, defines the absolute minimum joint angle error. Note that, for optical systems, this error varies volumetrically, i.e. it is not the same in all points of the observed volume. The rig can assist in precise volumetric error mapping, thus help calibrate the measurements inside the working envelope. Furthermore, the same procedure can reveal length estimation errors. Both tests B & C are dynamic. If the errors observed are significantly higher than test A, then further investigation could reveal a problematic algorithm in the gait capture system, e.g., look-ahead sampling. Besides positional and angular errors, dynamic tests can reveal timing errors, e.g., in stride time and the efficiency of critical software algorithms e.g., gait cycle detection. Given the assessed system's precision, one can decide if specific clinical gait measurements can be reliably performed. The following subsections present basic information for two of the main components utilized in the tests.

### *3.1. Gait Analysis System Under Test*

For illustration purposes, the Device Under Test is an optical, single-camera gait analysis system based on a smart-phone with specially developed software. The software identifies colored markers placed on hip, knee, ankle, captures their coordinates, and records them in a tabular file. Note that the camera is not calibrated, to demonstrate error factors. Our gait-capture application runs on android platform using OpenCV4.0, and records plane coordinates and video to file. New marker colors and max-min marker sizes can be taught-in at any time. Each frame is time-stamped using the system clock. Through scaling, the captured marker coordinates are transformed from pixel units to millimeters. Offset detection algorithms transform human gait cycle to rig data. For example, a human subject walking on a steady-speed treadmill is bound to infuse periodic horizontal axis displacement at his joints coordinates, as he can't achieve an absolute steady pace. Similarly, a treadmill with cushioning, induces vertical axis periodic displacements. Such "noise" is detected and excluded from the data downloaded to the rig.

### *3.2. Biomimetic Rig*

The rig bears one or two independent limbs, with four motorized orthogonal linear axes, two for each limb, controlled by a microprocessor, within a volume of 160x120x75cm. It is part of an ongoing study for the design and evaluation of various knee exoskeletical mechanisms. The limbs are interchangeable and length adjustable in order to match different physiologies. Each has three rotating joints: hip, knee, angle, and can be mounted on the rig at various orientations. The limbs are pathetic without motors or actuators, as they are designed to accept exoskeleton mechanisms for study. At this set of experiments, the specific limbs' knee joints are rotational, although, other sets of limbs could be used depending on the experiments' specifications, e.g. typical four ~ six bar mechanisms. The current rig setup focuses on knee flexion/extension angle (between femur and tibia) measurements. The rig emulates walking cycles or other sequences e.g., stand & walk, jog & run, squats, sitting & standing repetitive cycles, offering major advantages versus human subjects: memory, repeatability, stamina, adaptability, controlled variability. It can perform the same squat thousands of times, so that a gait analysis system can record it from various angles, distances, lighting conditions.

## 4. Evaluation

### *4.1. Test A*

It is designed to reveal static divergence, suitable for optical but not for inertial measurements. The setup uses:

1. A test limb that is adjusted to specific, known measurements (ankle-knee distance, hip-knee distance).
2. The biomimetic rig to drive the test limb to a specific, known angle (90° ankle-knee-hip angle).
3. The optical gait measurement system to capture the rig's stance for a few seconds. Three points are recorded, yielding one triangle per frame.

The scope is to determine the measured error against a trusted 90° angle. The same experiment could be conducted at various degrees, and various positions within the observed volume. In our case, we used a calibrated laser cross system to confirm the rig's correct placement at 90° (Figure 2 left). Note that the tablet camera is not fixed on a tripod, to demonstrate hand jitter which is vividly presented on Figure 2, centre-right, as offset multiple triangles. The test algorithm is: *Capture* an object of known spatial properties (width, height, angle) with the camera. *Compare* the measurement results to object's already known properties. Finally, extract differences and *categorize* possible errors, such as axes discrepancies, errors of perspective, angle errors, etc. Figure 2 offers an example of the above. The mean measured angle from the captured data (76 frames) is 88.5°, instead of 90°, revealing an error of ~1.5°, well below the 5° acceptable limit. For a thorough system characterization, the same experiment should be repeated for various angles, at different positions within the observation volume, which is beyond the scope of this paper.

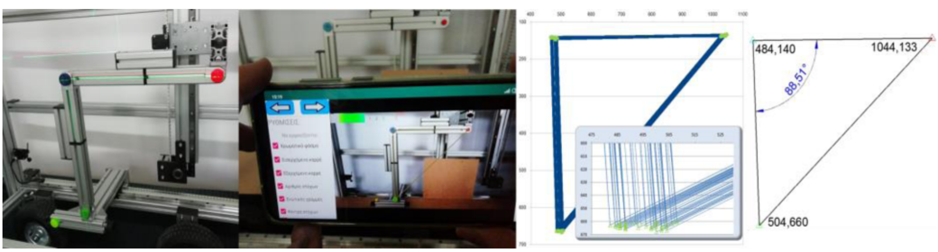


**Figure 2.** Test A. Left: partial photo of the rig posing. Centre-left: pose captured with our marker tracking software. Centre-right: visualization of 76 frames coordinates. Right: angle measurement on a single frame.

### *4.2. Test B*

It is dynamic, suitable for optical and / or inertial measurements. It is designed to reveal measurement divergence due to motion, and the accuracy of the gaps-filling estimation procedures. Setup:

1. Recorded, open source, human gait joint coordinates data (e.g. [17]) of known quality.
2. The biomimetic rig to emulate the recorded human gait.
3. The gait measurement system to capture the rig's gait. The camera's tripod is placed at a distance of 130cm away from the rig.

If the quality of the data which will drive the rig is not known, simple tests can illustrate the precision/variability of the data. In this example, the hip-knee distance variation is approximately 30.6mm, as shown in Figure 3 (left) which displays three pairs of coordinates per frame (of the hip, knee and ankle). The limb(s) of the biomimetic rig are continuously driven with the gait data. The gait is then captured with the optical system and the results are compared to initial data, in order to assess differences. By plotting the initial and captured frames per gait cycle, in different colors (e.g., grey versus red), with the aid of a design platform, the errors "pop-up", i.e. become apparent even to the untrained eye (Figure 3, right). Note the increasing distortion / noise towards the far ends of the gait cycle, as represented by the "misplacement" of captured ankles (red dots) against the original data. Plotting also facilitates fast, indicative measurements, with the ability to isolate frames of particular interest. In this example, measurements at selected frames reveal spatial errors around 24mm and angular deviations around 2° which are typical for non-calibrated cameras. Normally, to assess the optical-instrument-induced-variability, statistical analysis and point-by-point comparisons can be used as illustrated in [18].

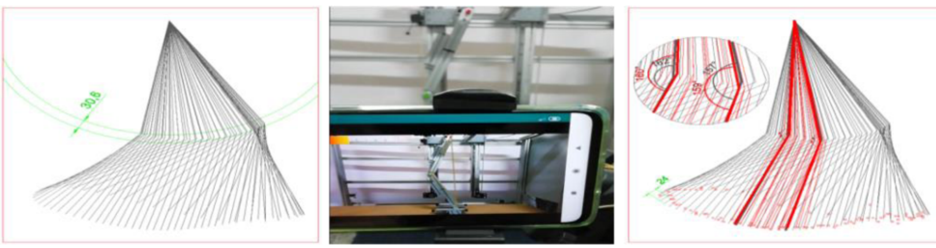


**Figure 3**. Test B. Left: initial data visualized. Centre: biomimetic rig emulating walk. Right: captured data (red) superimposed on initial data (grey). Measurements on selected frames.

*4.3. Test C*

It is a dynamic test, suitable for optical and inertial measurements, performed with a human subject, designed to reveal divergence by magnifying error components. Setup:

1. A human volunteer with attached markers.
2. A treadmill for the volunteer, so as to keep the capture camera steady.
3. The optical gait measurement system to capture the human's gait.
4. The biomimetic rig to emulate the recorded human gait.
5. The same gait measurement system to capture the rig's gait.

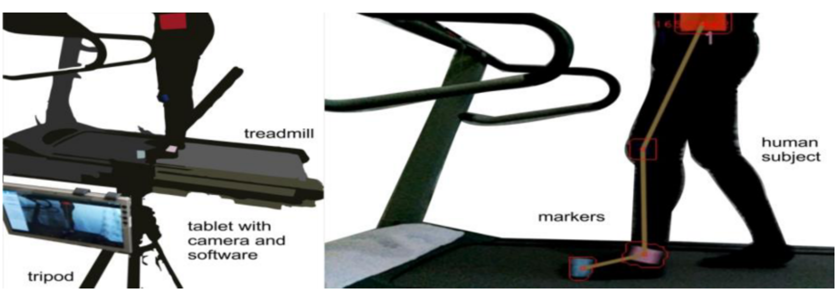


**Figure 4.** Left: Subject on treadmill, tablet on tripod. Right: Close-up of tablet monitor with markers and connecting lines. Background has been obscured afterwards.

An example is exhibited in Figures 4~6. The camera of the measuring system captures the sagittal plane at a distance of approximately 130cm from the treadmill. It is noted that the setup includes controlled light sources to help reduce shadows on markers. The male volunteer with height 182cm, 75kg weight, 45cm angle-knee distance, and 53cm knee-hip distance, walks for a few minutes on the treadmill, enough for the gait system to capture several complete gait cycles. Tabular joint data are analyzed, transformed and downloaded to the biomimetic rig to drive the limbs.

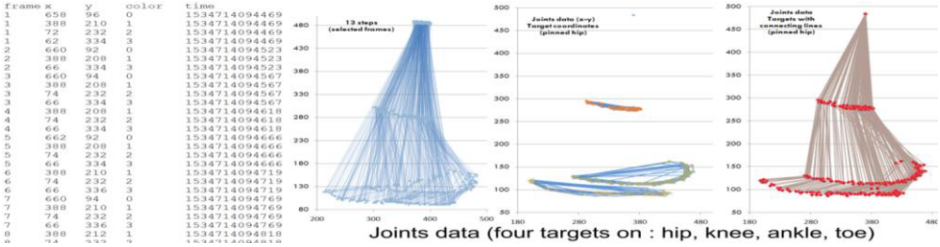


**Figure 5.** Test C. Data from human subject. Left: walking data sample as captured using 4 targets on left foot. Right: selected frames from the swing stage, visualized after processing.

**Figure 6.** Test C. Left: selected angle measurements from human captured swing stage. Centre: Rig walks. Right: visualization and measurements on selected frames.

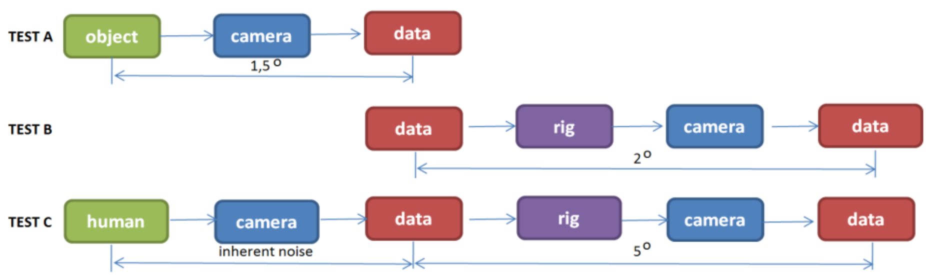


**Figure 7.** Error components

In Figure 6 left, note that the hip-knee distance from the captured human gait varies approximately 20.4mm. The rig's gait is then captured with the same optical system. The rig's gait data are plotted as in test B. Compared against the human gait, they reveal satisfactory fit: knee flexion/extension angular error reaches, but does not exceed, the 5° limit. In this case the initial hypothesis would be confirmed, if 5° errors were satisfactory for diagnosing that specific ailment, or rejected otherwise. In our particular example, the difference in angular errors (2° versus 5°), between test B & C, reveals the effect of inherent noise in the "camera plus markers plus software" system. In test C, this "noise" is added twice (Figure 7), given that the data used in test B are from significantly smaller variability.

## 5. Discussion

In this paper, we discussed the error components in gait analysis systems and presented a methodology for assessing the intra-equipment variability. The main contribution is that we managed to exclude the human Intra-Subject variability, which up to now has been largely uncontrolled, unknown, and unmeasured, thus affecting the overall accuracy of the gait analysis [18]. The remaining variability is due to the rest factors (equipment + therapist), that can now be revealed, thus easier to control.

Furthermore, with the aid of a biomimetic rig, it is now feasible to duplicate human gait patterns from past analysis or from distant labs data, and study them repeatedly, using various software / hardware configurations.

Similar methodologies can find interesting uses. Experiments like Test B, based on biomimetic rigs, could assist in training A.I. neural networks for gait capture. For example, by repeating a known pathological gait on the rig multiple times, the A.I. system can receive new training data (coordinate streams or video files) [19], from various camera positions, along the sagittal, frontal and transversal planes, at different lighting conditions. The above training data are automatically tagged, since they derive from the same pathological gait and thus, supervised machine learning training can be highly facilitated. The efficiency and maturity of a trained A.I. system can be assessed by presenting data from new perspectives. Again, using the biomimetic rig, this process can be automated and run extensively. An experienced A.I. could later, identify specific pathological gaits, in public human environments.

The same methodology can be adapted to other needs. E.g., gait labs/clinics, that will focus on the application of exoskeletical mechanisms, could be assisted by the biomimetic rigs, in the customization and tuning phases of such mechanisms, as much as possible, prior to the patients' visit (thus minimizing initial discomfort and fatigue). I.e., the first series of customization can be performed on the test rig, with the aim of reducing the differences (error components) between the pathological and the standard gait.

## 6. Conclusion

For assessing gait capture systems and labs, the human gait cycle variability (intra-subject) can be minimized by substituting the human subject with a robotic device. With the presented methodology, even low-cost, single camera systems can easily be benchmarked, without resulting to Golden standard systems, and thus may be used for certain gait analysis tasks within their specifications.

Identification of errors and variability in posture measurements can be accomplished with static tests, such as test A. Errors and variability in gait cycle characteristics estimation can be studied with dynamic tests, such as test B and C. Intra-Equipment variability can be amplified by closing the loop, i.e., by repeating the motion capture analysis twice within the same set of experiments, as in test C. The presented tests and measurements are just indicative and not limiting the possible tests and measurements that could be produced by the same or other setups.

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## References

[1] Perry, J., Burnfield, J., "Gait Analysis, Normal and Pathological Function",J Sports Sci Med.9(2), (2010), 353.
[2] Pulignano, G., Del Sindaco, D., Di Lenarda, A., Alunni, G., Senni, M., TArantini, L., Cioffi, G., Tinti M. D., Barbati, G., Minardi, G., Uguccioni, M., "Incremental Value of Gait Speed in Predicting Prognosis of Older Adults With Heart Failure: Insights From the IMAGE-HF Study", JACC: Heart Failure, vol 4, issue 4, (2016), 289-298.
[3] Muro-de-la-Herran, A., Garcia-Zapirain, B., Mendez-Zorrilla, A., "Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications", Sensors, 14, (2014), 3362-3394.
[4] Fried, A.V., Cwikel, J., Ring, H., Galinsky, D., "ELGAM, Extra laboratory gait assessment method: Identification of risk factors for falls among the elderly at home", Int. Disabil. Stud.,12,(1990), 161-164.
[5] Anderson, B., Mingqian, S., Vincent, T., Ye, W. "Mobile Gait Analysis Using Foot-Mounted UWB Sensors", (2019), Article No 73.
[6] Bovi, G., Rabuffetti, M., Mazzoleni, P., Ferrarin, M., "A multiple-task gait analysis approach: Kinematic, Kinetic, and EMG reference data for healthy young and adult subjects", Gait & Posture, Vol 33(1), (2011), 6-13
[7] Fonseca, M., Gasparutto, X., Leboeuf, F., Dumas, R., Armand, S., "Impact of knee marker misplacement on gait kinematics of children with cerebral palsy using the Conventional Gait Model-A sensitivity study", PLoS ONE 15(4), (2020).
[8] Gorton G. E., Hebert D. A., Gannotti M. E., "Assessment of the kinematic variability among 12 motion analysis laboratories" Gait posture, vol. 29, no 3, (2009), pp. 398-402,
[9] Bernardina, G.R.D., Cerveri, P., Barros, R.M.L., Marins, J.C.B., Silvatti, A.P., "Action Sport Cameras as an Instrument to Perform a 3D Underwater Motion Analysis" PLoS ONE 11(8), (2016).
[10] Rocha, A.P., Choupina, H.M.P., Vilas-Boas, M.C., Fernandes, J.M., Cunha, J.P.S, "System for automatic gait analysis based on a single RGB-D camera", PLoS ONE 13(8), (2018).
[11] Wang, Q.,Kurillo, G., Ofli, F., Bajcsy, R., "Evaluation of Pose Tracking Accuracy in the First and Second Generations of Microsoft Kinect", IEEE International Conference on Healthcare Informatics (ICHI), (20156), 380-389.
[12] Parks, M., Chien J.H., Siu K.C., "Development of a Mobile Motion Capture ($MO^2CA$) System for Future Military Application", Military Medicine. vol. 184, (2019), 3/4:65.
[13] Cohen, E.J., Bravi, R., Minciacchi, D., "3D reconstruction of human movement in a single projection by dynamic marker scalling", PLoS ONE 12(10), (2017).
[14] Sporri, J., Schiefermuller, C., Muller, E., "Collecting Kinematic Data on a Ski Track with Optoelectronic Stereophotogrammetry:A Methodological Study Assessing the Feasibility of Bringing the Biomechanics Lab to the Field", PLoS ONE 11(8), (2016).
[15] Dawe, R.J., Yu, L., Leurgans, S.E., Truty, T., Curran, T., Hausdorff, J.M., et al., "Expanding instrumented gait testing in the community setting: A portable, depth-sensing camera captures joint motion in older adults", PLoS ONE 14(5), (2019).
[16] Muller, B.,Ilg, W., Giese, M.A., Ludolph, N., "Validation of enhanced kinectsensor based motion capturing for gait assessment", PLoS ONE 12(4), (2017).
[17] Fukuchi, C., Fukuchi, R., Duarte, M., "A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals", PeerJ6, (2018), e4640.
[18] Schwartz, Michael H., Trost, Joyce P., Wervey, Roy A., "Measurement and Management of Errors in Quantitative Gait Data" Gait and Posture 20, (2004), pp. 196-203
[19] KidzinskiL., Yang B., Hicks J.L., Rajagopal A., Delp S.L, Schwartz M.H., "Deep neural networks enable quantitative movement analysis using single-camera videos", Nature Communications, 11, (2020), 4054.