Master's degree thesis

LOG950 Logistics

Examining the robustness of pose estimation(Openpose) in estimating human posture

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Figure

Table

Table of Contents

ABSTRACT

Background: While measuring the logistics ergonomics factors which are essential for ergonomics assessment have been mainly performed through wearable sensor-based devices lately, the vision-based methods which require only a standard camera to capture human pose have been progressing newly with the potential to use in the logistics ergonomics. OpenPose as a popular open-source technique among human pose estimation methods has been addressed in detecting body points and angle joints in ergonomics studies as well as human balance, human kinematics, and spatiotemporal gait in clinical settings; In most of these experiments, they only examined a single posture at a time. However, this study focuses on examining the performance of pose estimation (OpenPose) in detecting different types of postures both for walking (normal, slow, wide, limp, and short walking types) and balance experiments (normal and abnormal balance) by comparing the quantitative 2D spatiotemporal gait and balance measurements against a golden standard.

Method: We compared recordings of quantitative gait parameters in 24 walking trails and center of mass (CoM) displacement in 6 balance tests tracked from OpenPose and Motion capture which were performed by two participants. The comparisons were performed for videos captured by front and right-side cameras.

Results: Results from our research indicate that five out of six gait parameters namely the step time, stance time, and double support time measures calculated from the OpenPose correlate significantly to that of the motion capture system. However, the step width is the only parameter that designates a low correlation between them. Similarly, the results from logistic regression modeling showed insignificant relationship between these five gait parameters and the two pose capturing tools (Mocap and Openpose), while step width represented a relatively significant effect on them. The PLS-DA model (Partial Least Square Discriminant Analysis) demonstrated that gait variables extracted from OpenPose and Motion capture can be discriminated in clusters based on gait type with no major differences between OpenPose and Mocap. Also, the results from a two-group comparison test (Wilcoxon) on balance parameter (CoM values) between Mocap and OpenPose showed that the mean level of both samples is the same in four different balance trials, including three balance trials and one imbalanced experiment.

Conclusion: This study provides preliminary evidence that pose estimation (using OpenPose) could work as a tool for quantitative 2D spatiotemporal analyses of gait and balance as the key human movements to be referred to in ergonomics postural assessment.
The results suggest that pose estimation showed promising performance in discriminating among normal and abnormal postures as compared to the golden standard (Mocap) in gait and balance experiments. This reveals the potential for three-dimensional pose estimation using multicamera setups in future research.

Chapter 1

1. Introduction

1.1 Background and Motivation

Nowadays an integral part of supply chain management is to meet the demanding need of the business world to maximize yield while minimizing costs and achieving the highest possible quality. Achieving the agility, high productivity and high quality entails a competitive excellence in supply chain management. The strength of supply chain depends upon, among other things, the amount of operation's output which is affected by a bunch of factors including human factor as a significant driving force.

Ergonomics play a vital role in supporting the efficiency and productivity of supply chain operations through maintains the relationship between the company and the environmental aspects (Markus, 2008). A good workplace ergonomic system allows employees to operate at their highest level of productivity, quality, and efficiency. Ergonomics involves in the issues of the optimized design of work procedures, workplaces and tools, optimum operating mode, human intervention in automated systems, as well as the optimum performance of employees through training and motivation.

In the field of business logistics, the scope of ergonomics research is focusing on internal and external determinants of human which investigates the impact of work and the working environment on human through the physiological reactions of their bodies to the physical and mental demands. Through finding solutions that respect the possibilities as well as the hygienic, functional, and psychological requirements of employees, ergonomics led to reducing fatigue and potential acute or chronic health disorders (Beňo, 2013).

Workplace ergonomics importance arises mainly from the risk factors that can be threaten both the worker's health and the operation output which may be quite costly to both the employee and employer. An ergonomic approach can contribute to lower business costs, improved quality, and better workplace safety.

The evaluation of workplaces ergonomics investigates the risks of the physical interaction of people with their work environment which is settled in three areas including kinesiology (the study of human movement), biomechanics (the study of motion in living things) and the relation of kinesiology and biomechanics with workplace safety (Hazari, et al., 2021). Human movement and posture are two main factors that are considered in evaluation of ergonomics.

There are several observational methods of postural ergonomics assessment based on direct on-site observation or the video of workers when performing their jobs (Hignett & McAtamney, 2000) (Diego-Mas, et al., 2015) (Kee, 2021). Research proposals have been published at different stages regarding the improvement of these techniques.

Although observational methods are applicable in many work areas and easy to use, they depend on the judgement of the evaluator and also, they need a field expertise to handle a time-consuming manual analysis (Burdorf, et al., 1992) (Fagarasanu & Kumar, 2004).To fulfilling these problems researchers proposed the motion capture systems based on optical markers and wearable inertial sensors (Battini et al., 2014; Huang et al., 2020; Valero et al., 2016; Vignais et al., 2013) which have high accuracy for capturing human motions, but with drawbacks of expensive equipment, need for a skilled technician, and movement interference from body-attached markers/sensors (David, 2005; Trask et al., 2012).

A number of studies have used a low-cost Motion Capture (MoCap) system based on a Microsoft Kinect depth camera (Cai et al., 2019; Clark et al., 2019; Dutta, 2012; Xu and McGorry, 2015). Such solutions however have shown limitations such as body occlusions (Plantard et al., 2017b), low-quality of tracking from non-frontal views (Wei et al., 2015), and the elimination of neck twisting (Manghisi et al., 2017).

By the emergence of computer vision, vision-based approaches are making an outstanding headway for marker-less postural assessment as they provide the assessment availability from photos and videos captured by standard cameras (Bogo et al., 2016; Cao et al., 2017; Mehta et al., 2017; Rhodin et al., 2018; Yang et al., 2018; Zhou et al., 2017). While the vision-based methods used in ergonomics researches mainly focused on identifying major key points of the human body, in a recent study the joint angles were computed using OpenPose (Kim, et al., 2021). However, the results of studies on investigation of human kinematics considering the ergonomics context have yet to achieve a reliable level of accuracy. In this study the application of OpenPoes for assessing human balance, kinematics and spatiotemporal analysis of gait are presented. The difference of this research from the limited prior counterparts (Kim, et al., 2021) (Stenum, et al., 2021) (Li, et al., 2021)is twofold; This study has looked into the pose estimation algorithm (OpenPose) robustness

,first, in discriminating between the different types of walking, second, in detecting the imbalanced pose, compared to the measurement simultaneously derived from a golden standard.

1.2 Problem Statement

While measuring the logistics ergonomics factors which are essential for ergonomics assessment are mainly performed through wearable sensor-based devices lately, the vision-based methods which required only standard camera to capture human pose are progressing today with the potential to use in the logistics ergonomics. According to the literature (Kim, et al., 2021) (Li, et al., 2021) (Stenum, et al., 2021), addressing the robustness of pose estimation algorithms as the latest up-to-date methods for two-dimensional analysis of human pose, is needed to add the next achievement to the chain of forward research in logistics ergonomics context.

OpenPose as an opensource pose estimation algorithm has been studied on several objectives in recent years (Cao, et al., 2019) (Chen, 2019) (Kim, et al., 2021) (Li, et al., 2021); The findings represented the pose estimation application in detecting body points and angle joints in ergonomics researches as well as human balance and human kinematics and spatiotemporal gait in clinical settings when the experiments are designed for investigating one type of posture. However, this study focuses on analyzing the performance of pose estimation (OpenPose) in detecting different types of postures both for walking and balance experiments.

1.3 Goals and research question

Taking into consideration the vital role of postural evaluation in ergonomics within logistics, examining pose estimation as the state-of-the-art in human movement studies is targeted to be addressed in this study. The goal of this study is to experiment with OpenPose as a popular pose estimation algorithm to analyze the quantitative 2D spatiotemporal gait and balance.

This study is going to answer two different questions:

1. Could the pose estimation (OpenPose) detect changes across conditions for the characterization of different gait types?

2. Could the pose estimation (OpenPose) differentiate between abnormal balance pose as well as balance?

1.4 Outline

In Chapter 2, a relevant background information is introduced within both the supply chain logistics and the human pose fields. It is started by a brief explanation of logistics activities then pointed out the role of human movement studies in logistics. Then a thorough explanation of Human Pose Estimation is provided which is furthered by the Pose Estimation tools and summed up with a summary of related works in gait and balance posture. Chapter 3 describes the experimental settings and methodology used in this study as well as the statistical analysis done in two parts, gait, and balance. Chapter 4 documents the results produced during the research. Chapter 5 evaluates both the results and the applicability of our proposed method. Finally, Chapter 6 represents the conclusion for this thesis and suggestions for future work.

Chapter 2

2. Literature Review

This chapter contains the related researches in four parts, including the background of human movement studies in supply chain and logistics, a literature review on human pose estimation, an introduction on the tools for pose estimation and the background of gait and balance postures.

2.1 Supply chain background

The necessity of appointing the relationship between logistics and human, organizational, and social traits originates from the concept of logistics which involves people, materials, information, equipment, energy resources, as well as related knowledge and abilities, and can make satisfactory results (Loos, et al., 2016).

The extremely routine and manual nature of logistical activities may put employees at high risk of physical strain in working environment which entail gaining empirical insights into examining ergonomics within logistics (Gruchmann, et al., 2020). Manual labors in logistics workplace settings including warehouses and distribution centers mostly consist of repetitive physical movements throughout the day, such as twisting, lifting, bending, or sitting in an awkward position which expose the workers to overexertion, pain, and musculoskeletal disorders (Schmauder, 2013) (Günthner, et al., 2014).

For instance, “100 million European citizens suffer from chronic musculoskeletal pain and musculoskeletal disorders (MSDs), including 40 million workers who attribute their MSD directly to their work” (Hartvigsen, et al., 2018). According to Irastorza et al., work-related musculoskeletal disorders (WMSDs)constitute a significant contribution of work-related health problems in the European Union, which affect workers in different working sectors (Irastorza et al.,2010). Musculoskeletal conditions accounts for the second largest contributor to disability worldwide which are estimated to increase by the global population ages (Luttmannet al., 2003).

Ergonomics analyses make it possible to determine and assess repetitive workloads. Also, for evaluating work demands and environmental conditions, an ergonomics analysis offers recording physical stresses and body postures (Feldmann, et al., 2019). Using the result of this assessment can be reduced musculoskeletal disorders risk in long term.

The ergonomic assessment used to be done through observing the operators during work by the experts which were time consuming and required specialized ergonomists (Grooten & Johanssons, 2017). Today with the transition to Industry 4.0 and the introduction of new digital technology, monitoring of workers' physical and psychological well-being is supported through integrated platforms (Kadir & Broberg, 2020).

There are two popular devices for ergonomics assessment in workplaces namely Inertial Measurement Units (IMU) which is among the wearable-sensor based tools and Microsoft Kinect as a vision-based tool (Tee, et al., 2017) . Rocha-Ibarra et al. evaluated human ergonomics of a pick and place task using the Microsoft Kinect™ sensor to capture the postures of the subjects (Rocha-Ibarra, et al., 2021).

Fledmann et al. examined the ergonomic evaluation of body postures in the logistical activities of order picking systems by using a motion capturing system (Feldmann, et al., 2019).

The worker motion data for developing the concept of a Healthy Operator 4.0 (HO4.0) proposed by Sun et al. was collected through wearable devices (Sun, et al., 2020).

In several studies for the real-time monitoring of an operator’s activities wearable technologies were used (Kassner, et al., 2017) (Romero, et al., 2017) (Pavón, et al., 2018).

Other studies presented the use of deep learning to monitor an operator’s activities utilizing wearable devices for data collection (Zheng, et al., 2018) (Shoaib, et al., 2016). For the ergonomic assessment of physical workload, Onofrejova et al. used sensor-based wearable technologies and highlighted the ergonomic risk in industrial environment (Onofrejova, et al., 2022).

Another research addressed a variety of sensor-based wearable stretch sensors for human movement monitoring within workplace practices in physical ergonomics (Chander, et al., 2020). By using smart wearable devices Ciccarelli et al. provided a human work sustainability tool which consider all work-related ergonomic aspects including physical, cognitive, environmental, and organizational (Ciccarelli, et al., 2022).

Seo & Lee proposed a 2D image-based approach that automatically classify workers’ postures by using machine-learning algorithms which addressed the automating current postural ergonomic evaluation techniques (Seo & Lee, 2021).

Moreover, in another study a combination of computer vision approaches, and wearable sensors utilized to improve the accuracy of ergonomic risk detection as well as workers' locations (Yu, et al., 2019). To sum up, to date ergonomic assessment is performed through two categories of technologies including body-attached sensor-based approaches and vision-based approaches.

While the researchers mainly used the sensor-based methods in ergonomic assessment, limited researches have addressed the vision-based methods. Recognizing posture through devices connected to the body can be named as the main drawback of motion capturing wearable tools because they limit the type of motion recording at each trial as well as their requirement of specific settings. Moreover, the 2D image-based approach limitation refers to collecting dataset due to its requirement to large training data set, as a machine learning-based classification method (Yan, et al., 2017).

Human pose estimation as an emerging technology that measures human movement kinematics can be addressed these limitations by using only standard camera videos (Cao, et al., 2017) (Zago, et al., 2020) (Viswakumar, et al., 2019) (Kidziński, et al., 2020) (Sato, et al., 2019) (Fang, et al., 2017) (Mehdizadeh, et al., 2021) and freely available packages of training datasets (Stenum, et al., 2021).

Using a simple regular camera to capture the whole-body kinematics could considerably lessen the role of common techniques which are limited in terms of cost, technical expertise requirements, and obtrusiveness such as motion capture systems or wearable devices.

In a prior study, a pose estimation-based method (OpenPose) has been used for ergonomic postural assessment by measuring joint angles which is also validated against a reference Xsens inertial MoCap system (Kim, et al., 2021). However, this study is addressed the potential of the use of OpenPose as a tool for detecting spatiotemporal gait parameters as well as balance as the key human movements to be referred in ergonomics postural assessment.

2.2 Human pose estimation

Human Pose Estimation (HPE) is defined as estimating the configuration of the human body from an image (Sigal, 2014) (Xiong, et al., 2022). HPE detects and categorizes the poses of individual body elements and joints in images or videos. Most commonly, it performs through a model-based method the visualization and estimation of human body poses in 2D and 3D space. Afterward, when an image and video is entered to the model as input, the coordinates of these recognized body parts and joints are detected as output as well as a score representing the precision of the estimations.

This simple construction provides tremendous opportunity for measuring whole-body kinematics within almost any setting, with low costs of money, time, and effort.

The records of this branch of scientific endeavor date back to Aristotle in the fourth century BC, as the first known written quantitative analysis of walking (Baker, 2007) (Mündermann, et al., 2006).

Along with the advance of technology several modern tools for human movement analysis such as three-dimensional motion capture, instrumented gait mats, and a variety of wearable devices has been appeared in recent years.

It has abundance of growing applications ranging from human health (Stenum, et al., 2021) ,fall detection (Chen, et al., 2021) , sitting posture (Chen, 2019) , the field of sport and physical exercise (Badiola-Bengo & Mendez-Zorrilla , 2021), to remote patient monitoring (Sengupta, et al., 2020), security and surveillance (Penmetsa, et al., 2014) ,augmented and virtual reality (Marchand, et al., 2016) , robotics application (Zimmermann, et al., 2018) and many more.

Several recent studies on automatic human pose estimation used deep learning techniques by training the neural network using manually labeled image data and then compute the individual posture, including joint centers and skeletons (Toshev & Szegedy, 2014) (Wei, et al., 2016) (Papandreou, et al., 2018).

Deep-learning-based methods initially have launched with 2D pose estimation to estimate individual joint points from 2D RGB images, and progressed with 3D pose estimation, which estimates the 3D human joint locations directly using a single algorithm (Chen & Ramanan, 2017) (Pavlakos, et al., 2018) (Moon, et al., 2019) (Rhodin, et al., 2018) (Pavllo, et al., 2019). Recently, pose estimation has been applied widely in human gait classification and recognition (Sato, et al., 2019) (Spehr, et al., 2012) (Kwolek, et al., 2019).Also, the use of pose estimation in quantifying spatiotemporal and kinematic gait features has been showed promising results (Stenum, et al., 2021).

Previous studies on gait analysis mainly used two-dimensional pose estimation techniques to extract capture gait parameters such as step lengths, step width, step time, stride length on a single gait type (Aung, et al., 2019) (Ng, et al., 2020) (Sato, et al., 2019) (Shin, et al., 2021)

(Stenum, et al., 2021) (Mehdizadeh, et al., 2021). However, the need of investigating the ability of pose tracking algorithms in detecting different gait types persists.

On the one hand, Seethapathi et al. investigated deep-learning-based human pose tracking algorithms from the aspect of the human movement science and presented that these algorithms did not set up the arrangement of the quantities which matters in movement science (Seethapathi, et al., 2019). Hence, Nakano et al. claimed that that in human movement studies such as sports biomechanics or clinical biomechanics which mainly involves the functional mechanisms (included ergonomic factors) a combination of free available deep-learning-based packages and the principles of conventional motion capture systems such as camera calibration or kinematic data processing methods could be used (Nakano, et al., 2020). For example, OpenPose as one of the most popular open-source pose estimation technologies (Cao, et al., 2019) is considered due to its ease of use.

On the other hand, measuring human gait and movement using the modern tools limits their applicability due to not only their requirements including clinical settings and time consuming, but also the high prices and expertise-based usage. In the next section several movement assessment tools are elaborated.

2.3 Pose estimation tools applied to gait research

The recent progress in movement assessment tools ranges from the Kinect sensor (Microsoft, Redmond, WA) (Mehdizadeh, et al., 2020) (Latorre, et al., 2019) (Dolatabadi, et al., 2017) (Springer & Seligmann, 2016) (Mehdizadeh, et al., 2020) (Dolatabadi, et al., 2014) to video-based pose estimation as an achievement of computer vision technology (Anon., u.d.; Andriluka, et al., 2014) (Cao, et al., 2019) (Insafutdinov, et al., 2016) (Pishchulin, et al., 2016) (Martinez, et al., 2017) (Toshev & Szegedy, 2014) (Mathis, et al., 2018) (Nath, et al., 2019).

Recently video-based tools have been used to assess human walking through pose tracking algorithms (Cao, et al., 2017) (Zago, et al., 2020) (Viswakumar, et al., 2019) (Kidziński, et al., 2020) (Sato, et al., 2019) (Fang, et al., 2017) (Mehdizadeh, et al., 2021).

Detection of body key points in these algorithms is based on trained networks from annotated videos of freely available large datasets including MPII (Andriluka, et al., 2014) and COCO (Context, 2014). Some of the gait parameters that have been measured with pose estimation under different conditions include step lengths, step width, step time, stride length, gait velocity, and cadence (Sato, et al., 2019) (Aung, et al., 2019) (Ng, et al., 2020).

In the last decade different pose tracking algorithms have been issued such as OpenPose (Cao, et al., 2017), DeepLabCut (Mathis, et al., 2018), DeepPose (Toshev & Szegedy, 2014), DeeperCut (Insafutdinov, et al., 2016), Alpha-Pose (Fang, et al., 2017), ArtTrack (Insafutdinov, et al., 2017). Most of these techniques have models that work relatively well for humans and are freely available. OpenPose as a state-of-the-art and open-source model is used for multi-person 2D pose estimation in real-time.

Several studies have investigated the validity of pose tracking algorithms. The reliability and validity of motion analysis during squat using a pose tracking algorithm (OpenPose) is demonstrated by Ota et al. (Ota, et al., 2020).

The need for comparisons of these techniques against simultaneously collected, gold-standard measurements are addressed in the following studies. The findings obtained by Mehdizadeh et. al in validating gait parameters calculated by three pose algorithms against gold standard methods in older adults revealed that AlphaPose and Detectron had the highest agreement while OpenPose had the lowest agreement in their assessment conditions (Mehdizadeh, et al., 2021).

However, Stenum et al. investigated the validity of a pose tracking algorithm (OpenPose) against gold-standard measurements and proved that OpenPose can provide estimates of many human gait parameters with the accuracy and precision needed to detect changes in the gait pattern in healthy humans (Stenum, et al., 2021).

In another study, Åberg et. al evaluate the accuracy of gait parameters measurement estimated by marker-free video recordings of Timed Up-and-Go tests (TUG) supported by OpenPose in comparison with a Marker-based optoelectronic motion capture system as golden standard and found different percentages of agreements in the % absolute mean difference for different gait parameters ranging from less than 1.1 %, to 6% and 13% (Åberg, et al., 2021).

In this study a pre-trained network provided by Open-Pose is used due to its robustness and ease of use (Yadav, et al., 2019) (Cao, et al., 2019) (Stenum, et al., 2021) (Viswakumar, et al., 2019) (Anon., u.d.) (Ota, et al., 2020).

2.4 Balance posture

Although gait analysis using pose estimation algorithms has been studied intensively over the past decade, less is known about the performance of pose estimation algorithms on human balance posture.

Computing the Center of Mass as a measurement of balance has been proposed by Winter (Winter, 1995). Doheny et. al proposed a method for measuring the displacement of a person's Center of Mass using accelerometry to distinguish fallers from non-fallers (Doheny, et al., 2012). Dubois and Charpillet calculated the displacement of Center of Mass by a tracking marker-less method (Dubois & Charpillet, 2014).

In another study the 3D position of a Center of Mass of a human body were estimated using a deep learning model and by a set of multi-view images from RGB cameras (Kaichi, et al., 2018). A method based on a deep learning network was proposed by Wei and Dey et al, which estimated the Center of Mass through a CNN-based network and by using depth images from a single Microsoft Kinect RGB-D camera as input (Wei & Dey, 2019).

Li et. al measured Center of Mass and Center of Pressure as the balance parameters using OpenPose and successfully validated the method comparing to a motion capture tool (Li, et al., 2021). While OpenPose showed satisfactory performance in calculating the normal balance (Li, et al., 2021), its strength in detecting imbalanced postures is not known yet.

The aim of this study is to investigate the performance of a two-dimensional pose tracking algorithm (OpenPose) in detecting different gait types and imbalanced posture in comparison with a golden standard method (3D Motion Capture) regarding the accuracy of the measurements.

Chapter 3

3. DATA AND METHODS

Quantitative research involves analyzing and collecting data in a quantified way. Generally, it is used to search for patterns, averages, predictions, as well as causal relationships between variables under investigation (Bryman, 2012) .

Experimental research as a kind of quantitative research method follows a strict scientific research design. Through experiments, a hypothesis is tested or attempted to be proven. Method of this study is based on the quantitative technique and, in particular, it is an experimental research.

3.1 Data

Data collecting were performed through two experiments, walking trials and balance tests. In walking experiment totally, 36 records from 12 walking trials in two directions captured from pose estimation (OpenPose) and Mocap. The values of gait parameters got from averaging over the steps of each participant.

For the balance experiment, four datasets from different 30-seconds balance trials were provided, each consists of more than 850 observations derived from the Mocap recordings and videos of OpenPose.

3.2 Method

The study is conducted at the laboratory of SINTEF Digital, a research division in SINTEF, located in Trondheim, at the Department of Mathematics and Cybernetics, to assess the estimation of standard clinical gait parameters such as step length, step width, swing time, step time, stance time and double support time as well as center of mass displacement as a balance parameter with the use of pose estimation methods.

3.2.1 Participants

Due to the different gait and balance types as the aiming of data collecting for the experiments of this study, two participants were contributed who were asked to simulate the defined postures according to the protocol of the study. Each participant performed five different types of walking and two different types of balance trials. They agreed to be videotaped during the data collection period as an element of the study.

3.2.2 Motion capture system

Measurements of optical motion capture have long been regarded as one of the gold standards in the field of biomechanics within the research community. Regarding the validity of optical motion capture systems Yeo et al. suggested Qualisys for efficient and accurate measurements of gait analysis. In this study three-dimensional (3D) motion capture Qualisys with six cameras (Figure 1) was used to capture participants' motion at 200 Hz while they were wearing whole-body markers. A total of 39 markers were attached to the head (4), arms (7 on each), legs (12), torso (5), pelvis (4) during static and gait measurement (Figure 2). Qualisys QTM software was used to record and pre-process the walking trials.

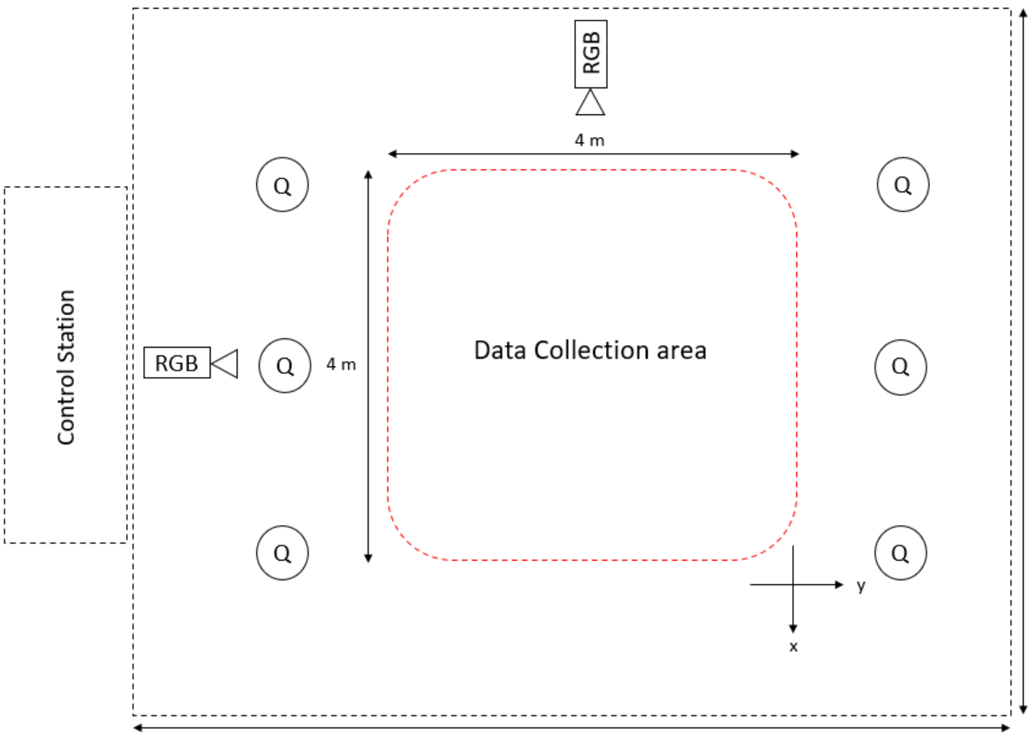

Figure 1 : Laboratory setting, **Q** Qualisys cameras, **RGB** GoPro cameras

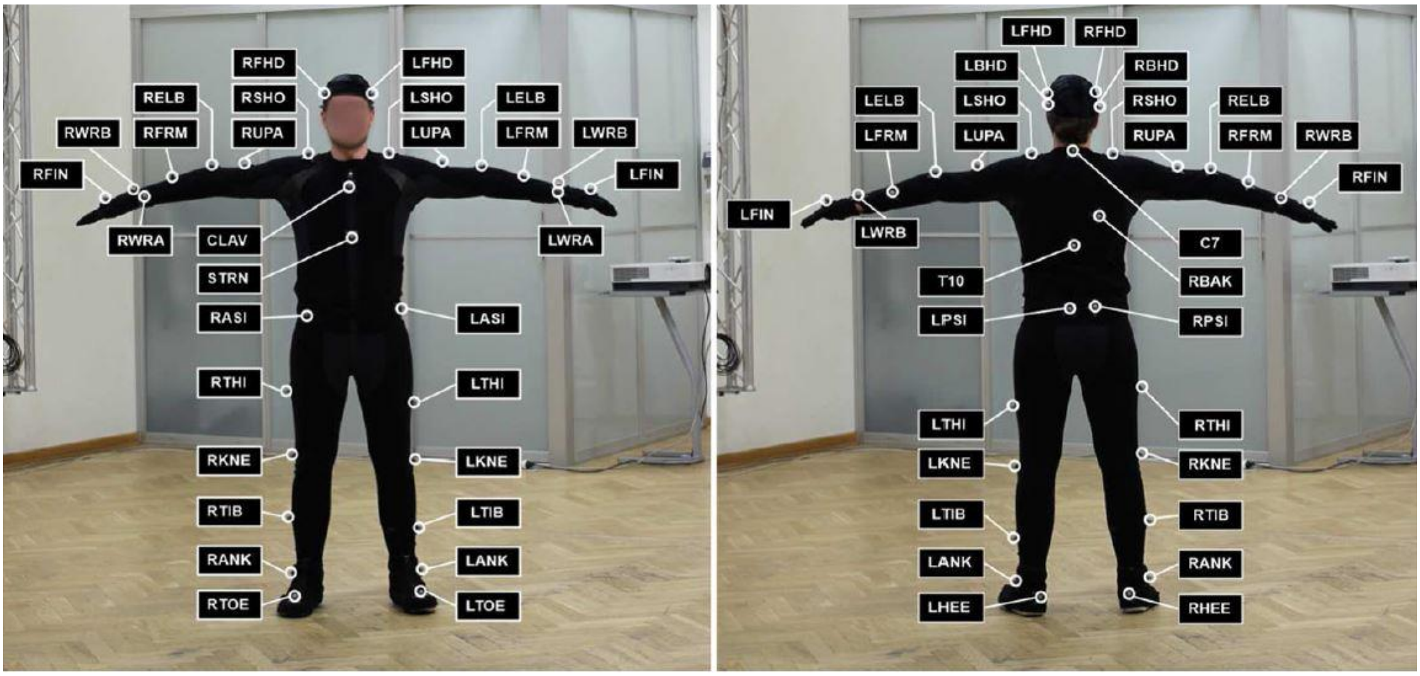

Figure 2: Qualisys full-body marker set *(Kwolek, et al., 2019)*

3.2.3 Cameras

With the aim of using regular video cameras, two Go Pro Hero cameras were used to record video from sagittal and frontal views at 60Hz with a 1080p resolution. The cameras were placed centered and outside of the 4x4 meter recording space (Figure 1), for footage from front and left side.

From the walking trials and balance tests of participants, 30 videos from each of the front and right-side cameras including 12 walking trials in two directions and four balance test trials were obtained. Likewise, 30 motion capture recordings were captured with the same performed experiment.

3.2.4 Experimental protocol

In several studies the short physical performance battery (SPPB) has been proved to be a reliable tool for measuring gait and balance parameters, since it is simple to use, short, and standardized, it should be used in clinical settings(Veronese et al., 2014; Volpato et al., 2011) . Another study showed that the SPPB is faster and simpler to use comparing to the currently available gait and balance screening tools (Lauretani et al., 2019). Hence, for assessing pose estimation in a standard clinical setting, as the suggestion of several physiotherapists who got involved in this study, SPPB test was conducted for providing the reference metrics to be compared between 2D video-based pose estimation algorithms and 3D golden standard motion capture system. Participants were asked to complete two tasks of SPPB test: assessment of standing balance and 4-m walking back and forth per trial (Figure *3*). Laboratory settings are shown in (Figure 1).

Following the SPPB protocol, it was determined that several simulated gait and balance manners be performed by each participant. These motion tasks included normal and disturbed balance tests as well as normal and several abnormal gait trials. Walking slow, short, wide, and limp comprised the performances in simulating the abnormal gait tests. In total 18 records in walking trials were captured by both instruments (3D Mocap and 2D video-based cameras) simultaneously.

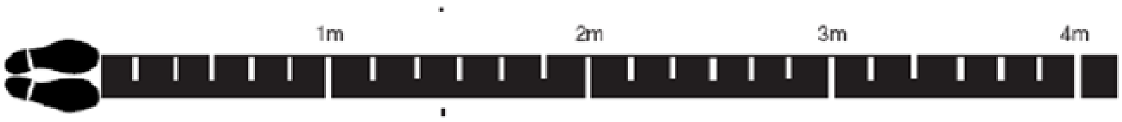

Figure 3) Gait test path according to SPPB protocol

The standing balance test was performed in three phases; First, participants were asked to remain standing with their feet as close together as possible, second, in a semi-tandem position, and finally in a tandem position. Each position had to be held for 10 s (Figure *4*).

One 30-seconds abnormal balance test simulated by each participant and three normal balance tests performed which were recorded concurrently by Motion capture and Gopro cameras. By extracting the displacement of COM from the recordings, four different datasets each consists of more than 850 observations per system provided.

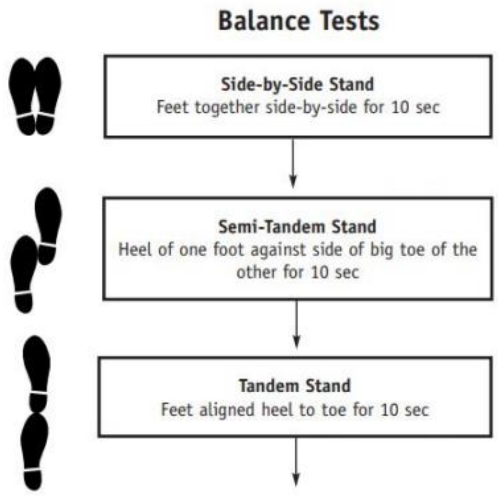

Figure 4) Balance test according to SPPB protocol

3.2.5 Video pose estimation (Data processing)

Data pre-processing involved labelling and gap-filling of motion capture recordings for all trials and clipping and pose estimation processing for all video recordings. Video clipping was done to extract individual 4m walk trials from first to last step on each direction (away from frontal plane camera, and towards frontal plane camera). The recorded videos from frontal and sagittal views were processed using Open Pose in a Python script on Google Collaborative. Scripts used to process video data were developed and used by (Stenum, et al., 2021) and are freely available at https://github.com/janstenum/GaitAnalysis-PoseEstimation.

Motion capture was processed in MATLAB (Mathworks 2021) to extract spatiotemporal gait metrics from 3D marker data. For motion capture and the left views of OpenPose, timings of gait events (heel-strikes and toe-offs), as well as spatiotemporal gait metrics (step time, stance time, swing time, double support time, step length, and gait speed) were separately determined.

3.2.6 Gait and balance parameters

Gait and balance parameters were calculated using the recorded gait and balance from 3D Mocap Qualysis and 2D Openpose. The calculated gait variables include Step time (duration in seconds between consecutive bilateral heel-strikes), Stance time(duration in seconds between heel-strike and toe-off of the same leg), Swing time (duration in seconds between toe-off and heel-strike of the same leg), Double support time (duration in seconds between heel-strike of one leg and toe-off of the contralateral leg) and Step length (anterior-posterior distance in meters between left and right ankle markers (motion capture) or ankle key points (OpenPose) at heel-strike), Step width(medial-lateral distance in meters between left and right ankle markers (motion capture) or ankle key points (OpenPose) at heel-strike) and Gait speed(step length divided by step time).

Analysis of the balance test was done through the trajectory of the Center of Mass (CoM). CoM was estimated with the segmental kinematics method (Winter, 1990), where inertial parameters of body segments allow the computation of the body center of mass through the weighted average of the CoM of each segment. Anthropometric data, including the mass distribution within the segments and the location of their CoM, were taken from (Wiley & Sons, 1990).

Processing of motion capture data and estimation of CoM trajectory was done in custom-made Python scripts. Processing of video and pose estimation data was done using a customized version of the tools described in (Stenum, et al., 2021) and custom-made MATLAB scripts.

3.3 Statistical analysis

3.3.1 Gait analysis

Analysis of the gait in this study is done in four parts. First, an overall view of the gait data from Motion capture and OpenPose is described shortly, the results are reported in descriptive analysis section.

Then, correlation analysis is used to determine the correlation between the gait variables calculated from the video and from the motion capture system as the golden standard, the results are reported in correlation analysis section.

In the next part, logistic regression is used for comparing the estimation of gait parameters (step time, stance time, swing time, double support time, step length, and step width) between the gold standard motion capture and pose estimation. For that, logistic regression modeling is developed in several stages. Logistic Regression is from a family of generalized linear models (GLM). It is a binary classification algorithm used when the response variable is binary (1 or 0) which includes dependent variables that are non-normal. This method without considering the normality assumption for the predictor variables, predict the values of response variable (David W. Hosmer, et al., 2013). We used it to find the best fitting and clinically interpretable model to describe the relationship between the type of system (Mocap or OpenPose) and all six numeric gait parameters (step time, stance time, swing time, double support time, step length, and step width) (David W. Hosmer, et al., 2013).

The system type (Mocap or OpenPose) is considered as the dependent (response) binary variable and six gait parameters are defined as independent variables in the model. For this purpose, the family argument in GLM function is set to **binomial()** .

In a GLM model a coefficient is assigned to each independent variable and the model is written as below:

$$system.type = \beta_0 + \beta_1 * step.time + \beta_2 * stance.time + \beta_3 * swing.time + \beta_4 * DS.time + \beta_5 * step.length + \beta_6 * step.width$$

In the above model the null hypothesis (H_0) and the alternative hypothesis for each independent variable (H_1) are written as follow:

$$\begin{cases} H_0 : \beta_i = 0 \\ H_1 : \beta_i \neq 0 \end{cases}, \quad i = 0, 1, \dots, 6$$

The hypothesis $\beta_i = 0$ means that the independent variable corresponding to this coefficient is not significant in the model. In other words, the independent variable has no significant relationship with the response variable and if the p-value resulting from the GLM test is greater than the significance level (0.05) the null hypothesis is accepted. Alternative hypothesis represents that there is a statistically significant association between independent variable under study and the type of system. The results are reported in logistic regression section.

Finally, for investigating the detection possibility of the pose tracking algorithm among different type of gait, PLSDA (Partial least squares discriminant analysis) technique is used. The gait measures used in the statistical analysis got from averaging over the steps of each participant. The significance level in all statistical analysis in this study is set to 0.05.

3.3.2 Balance analysis

For comparing the mean of two sample of CoM displacement which is considered as the balance parameter, hypothesis testing was performed. For that, first, to determine the appropriate type of statistical two-sample test, the test requirements including the normality test (M.Jarque & K.Bera, 1980) was checked. Then, the mean of each group is compared through Wilcoxon test. For that the null hypothesis (H_0) and the alternative hypothesis are written as follow:

$$\begin{cases} H_0 : \mu_1 = \mu_2 \\ H_1 : \mu_1 \neq \mu_2 \end{cases}$$

μ_1 refers to mean of CoM from Motion capture and μ_2 indicates mean of CoM from OpenPose in each of the defined balance tests. The results are reported in balance results section.

Chapter 4

4. Result

Snapshot of the output of balance and walking trials from both systems is presented in

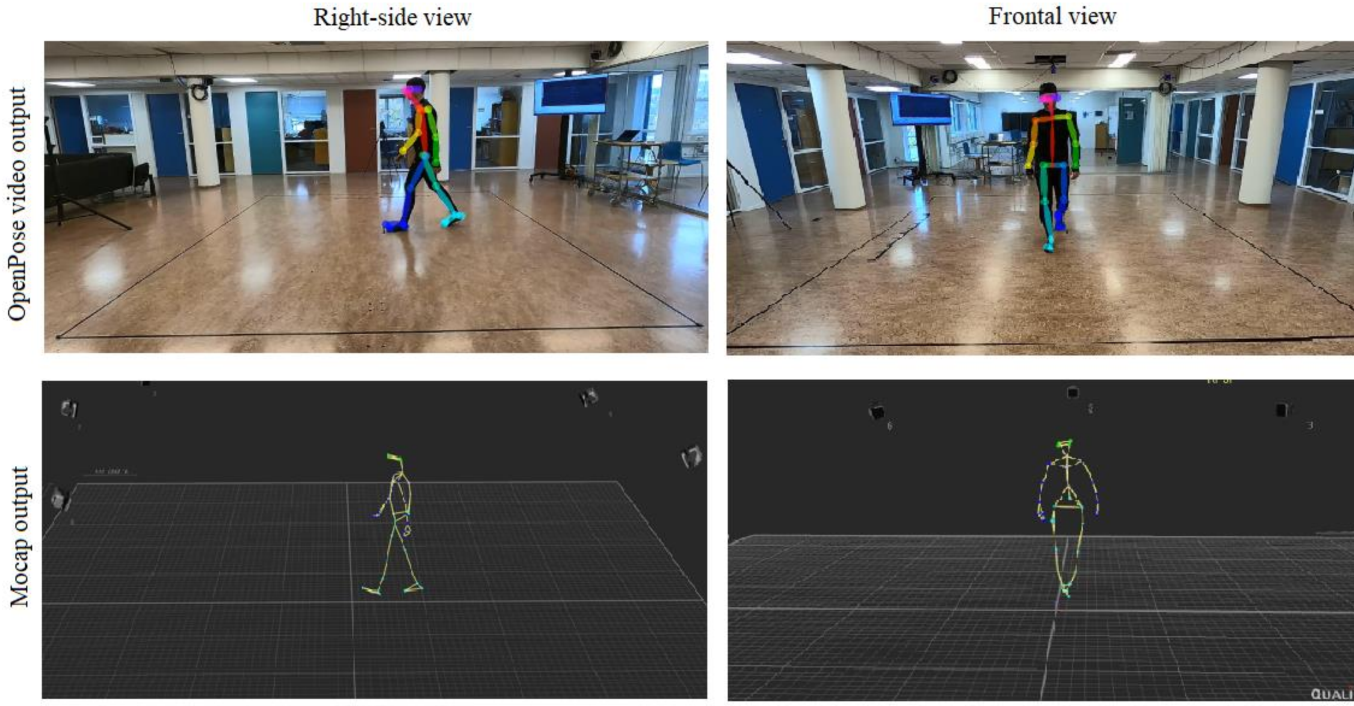

Figure 5 and **Figure 6** .

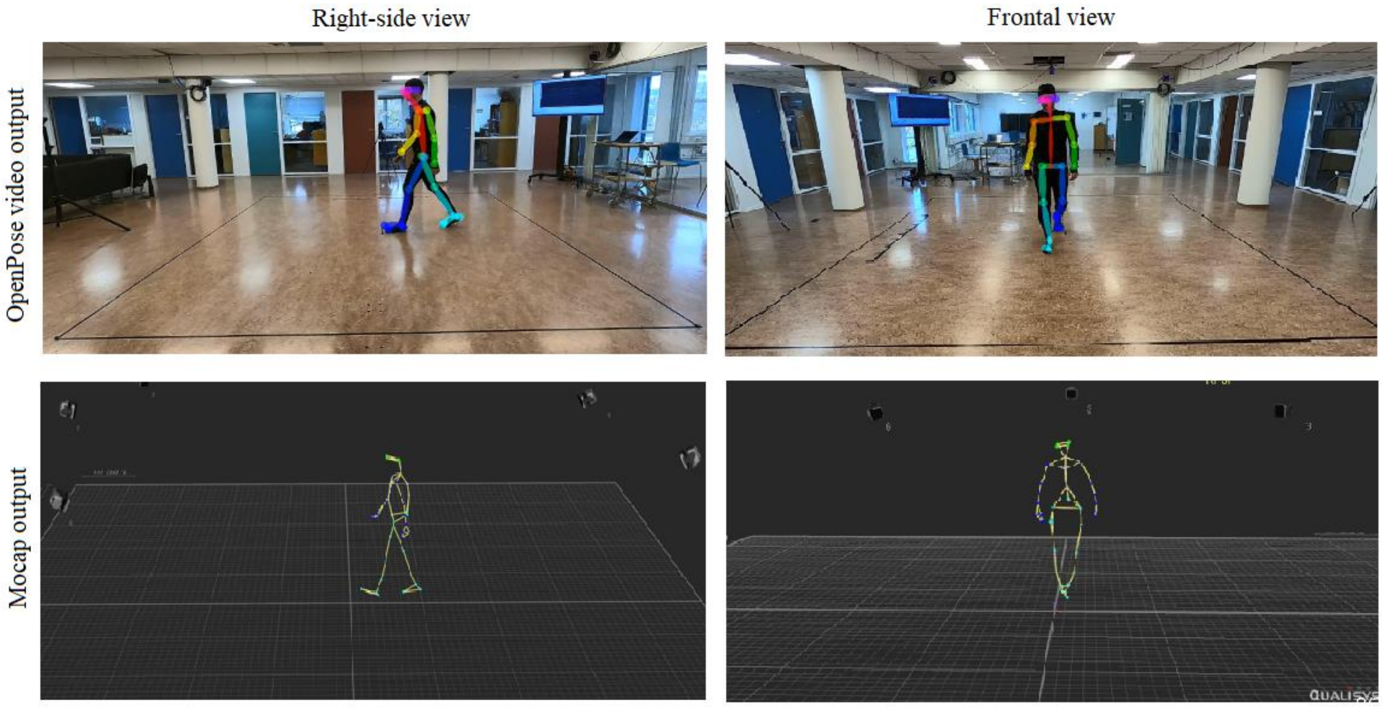

Figure 5) View walks from pose tracking video and Motion capture record of the front and right-side camera

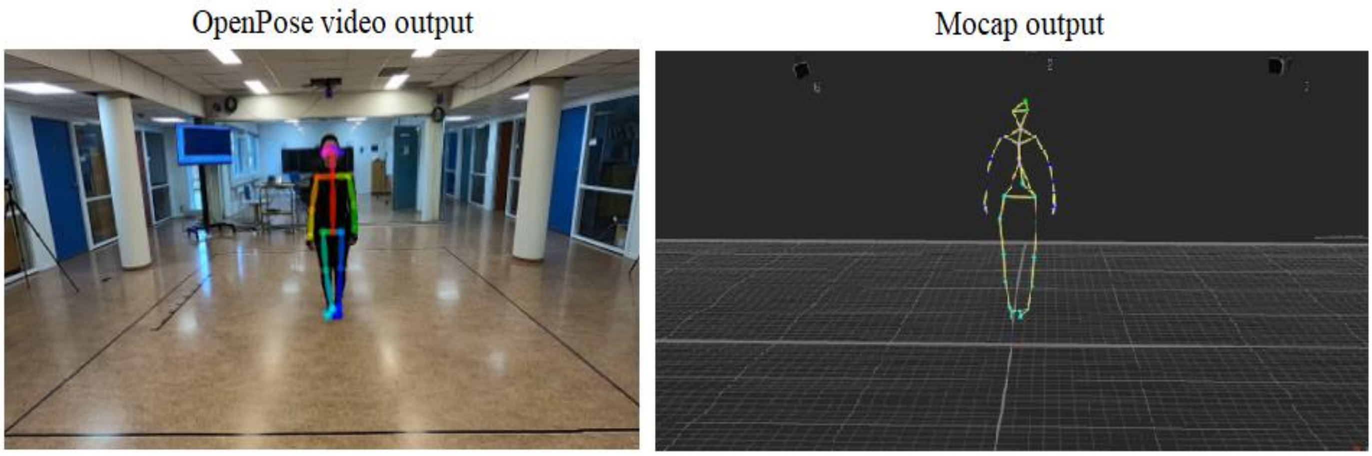

Figure 6) Balance test views of pose tracking video and Motion capture recorded from front camera

4.1 Gait results

4.1.1 Descriptive Analysis

The average values of the six gait measures for the Motion capture (Qualisys) and pose tracking algorithm (OpenPose) are presented in **Error! Reference source not found.** and Figure 7. The group mean difference as a measure of bias between measurement systems and the group mean absolute difference as a measure of the error between them were also calculated shown in the same table.

Table 1 Gait variables values calculated for the motion capture and video data using OpenPose algorithm

Gait parameters	N	Mean ± SD		Mean ± SD	Mean ± SD
		MC(3D)	OP(2D)	MC - OP	|MC - OP|
Step Time (s)	36	0,71 ± 0,21	0,72 ± 0,21	0,00 ± 0,03	0,02 ± 0,02
Stance Time (s)	36	0,99 ± 0,35	0,99 ± 0,33	0,00 ± 0,05	0,04 ± 0,03
Swing Time (s)	36	0,43 ± 0,10	0,44 ± 0,10	0,00 ± 0,04	0,03 ± 0,03
Double support time (s)	36	0,28 ± 0,15	0,27 ± 0,13	0,01 ± 0,04	0,03 ± 0,03
Step Length (m)	36	0,31 ± 0,17	0,33 ± 0,17	-0,02 ± 0,07	0,04 ± 0,06
Step Width (m)	36	0,27 ± 0,08	0,21 ± 0,08	0,06 ± 0,08	0,07 ± 0,07

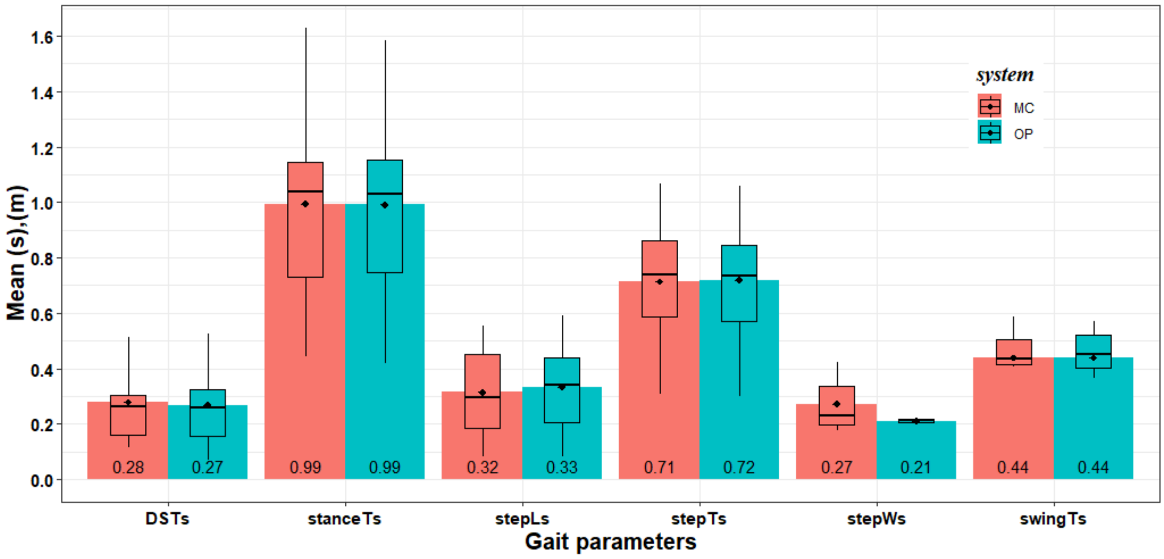

Figure 7) Comparison of gait parameters between Motion capture and OpenPose using means of all step trials

4.1.2 Correlation Analysis

For representing the strength of the relationship between the gait parameters derived from the video and from the inertial motion capture system as the gold standard correlation calculation was done. To find the appropriate type of correlation in this case, the normality assumption of the gait parameters was evaluated using the Shapiro-Wilks test. The p-value of all gait parameters are reported in Table 2.

Table 2) Results of Shapiro-Wilks test of gait variables calculated from the motion capture and from the Open Pose tracking; *, significant p < 0,05

Gait parameters	p-value	
	MC(3D)	OP(2D)
Step Time (s)	0,79	0,62
Stance Time (s)	0,61	0,76

Swing Time (s)	0,01*	0,01*
Double support time (s)	0,01*	0,01*
Step Length (m)	0,1	0,1
Step Width (m)	0,01*	0,01*

As it is demonstrated in the above table having three of gait parameters less than 0.05, i.e., showing they are significant, the hypothesis of normality is rejected, which is the case that determined to use the Spearman's correlation. Accordingly, Spearman correlation analysis was used.

Table 3) Results of correlation analysis between gait variables calculated from the motion capture and from the OpenPose tracking; *, significant p < 0,05

Gait parameters	**Spearman correlation**	
	R_s	p-value
Step Time(s)	0,98	< 0,001*
Stance Time(s)	0,98	< 0,001*
Swing Time(s)	0,74	< 0,001*
Double support time(s)	0,97	< 0,001*
Step Length(m)	0,85	< 0,001*
Step Width(m)	0,29	0,23

Spearman's correlation results for the gait variables from the motion capture and the OpenPose tracking are presented in Table 3 and Figure 8. It is observed that five out of six gait parameters show strong correlations namely the step time, stance time and double support time measures with very high correlation values (Rs > 0.9, p-value < 0.001), step length and swing time variables with high correlations (Rs > 0.7, p-value < 0.001). However, the step width is the only parameter that designates low correlation and insignificant p-value (Rs = 0.29, p-value = 0.23) possibly due to the effect of frontal plane video perspective on the scaling of pixels to meters, since the values obtained from the pose estimation are dimensionless and cannot be directly compared with motion capture values; This conversion of pixels to meters introduced error.

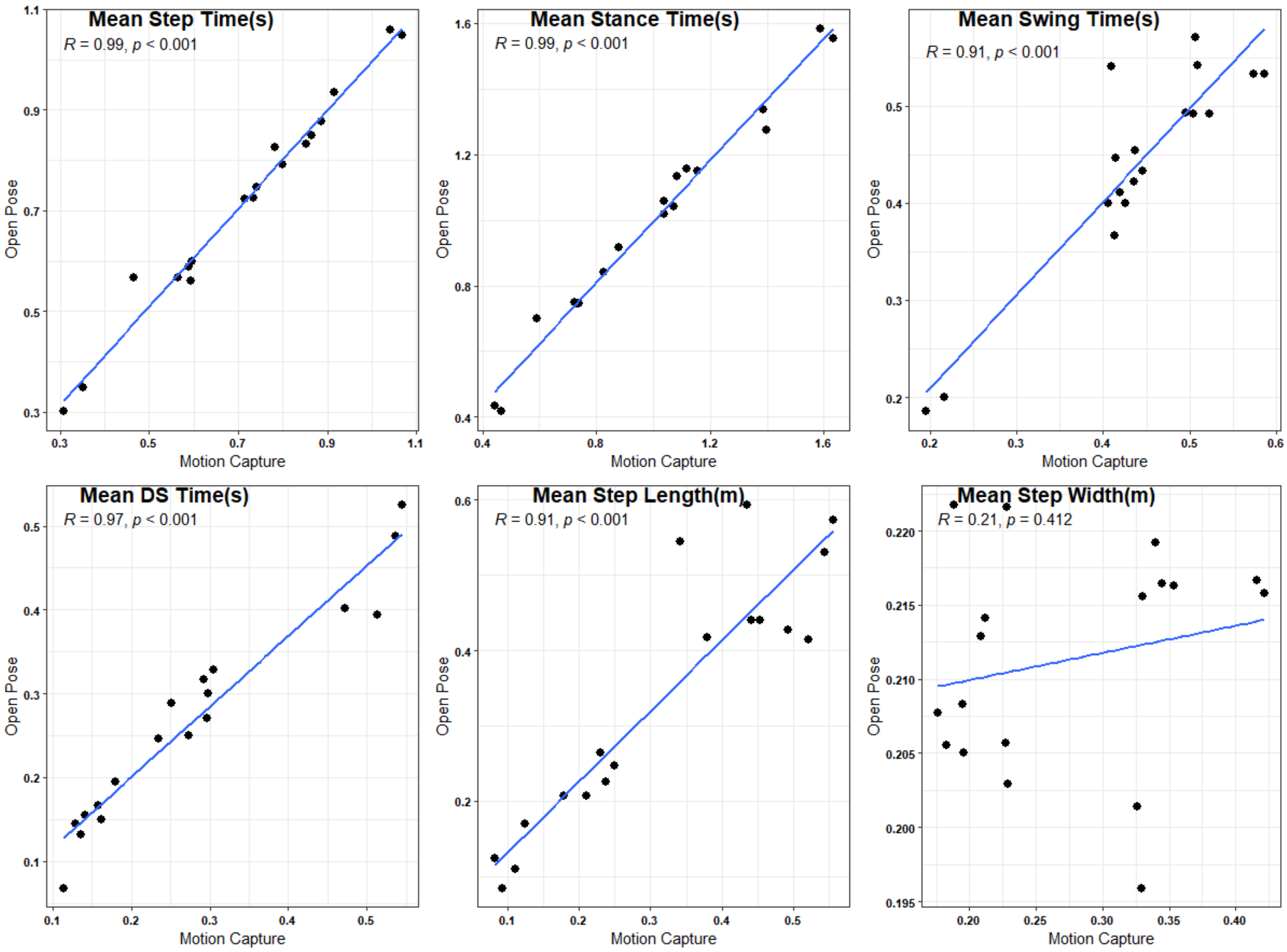

Figure 8) Scatter plots for all gait parameters including mean of steps captured from Motion Capture and OpenPose; The blue line is the fitted line. The correlation coefficient and p-value are shown in the figures.

4.1.3 Logistic Regression

The common way of fitting a logistic regression model is that all the independent variables enter the model at the same time and tested against the alternative hypothesis but since the information (number of observations) in this study are limited, the better way of studying the relationships is the conservative approach. Of course, a complete model with all the independent variables entering the model at the same time is fitted after the forward approach to make sure about the effect of each independent variable's presence on the response variable in the model.

To determine the effect of each predictor on the response variable, a forward logistic regression approach is used such that the predictors are added to the model in turn.

First, the one-predictor model using step time was fitted.

Table 4) Results of Logistic regression model / one-predictor in first turn

Predictors	System Estimate	Statistic	p-value
(Intercept)	0.92	-0.07	**0.947**
Step Time	0.12	0.07	**0.945**
Observations	36		

The result of logistical regression (Table 4) shows that the p-values are significantly greater than 0.05, which states there is no statistically significant relationship between the system type and step time. Therefore, we strongly (p-value = 0,95) accept the null hypothesis for this variable, it approves that step time measures in both systems are statistically the same.

Then, the second predictor, stance time, is added to the model.

Table 5) Results of Logistic regression model / Two-predictor in second turn

Predictors	System Estimate	Statistic	p-value
(Intercept)	0.79	-0.19	**0.852**
Step Time	8.65	0.35	**0.725**
Stance Time	0.27	-0.35	**0.729**
Observations	36		

From the result (Table 5) it is observed that there is no association between any of the two predictors (stance time and step time) and the system type. Having the p-value > 0.7 for both of independent variables, lead to accepting the null hypothesis strongly. As looking at the results step time is still insignificant in the model even after entering stance time.

Next, in the third turn, the three-predictor model is fitted, by adding swing time parameter.

Table 6) Results of Logistic regression model / Three-predictor in third turn

Predictors	System Estimate	Statistic	p-value
(Intercept)	1.04	0.03	**0.979**
Step Time	167.21	0.51	**0.608**
Stance Time	0.09	-0.50	**0.615**
Swing Time	0.05	-0.38	**0.704**
Observations	36		

As it can be seen in Table 6, by adding the swing time to the model, the p-values for all three predictors still are highly insignificant, i.e., the level of step time, stance time and swing time between Mocap and OpenPose are equal.

Then, double support time as the next independent variable is inserted to the model.

Table 7) Results of Logistic regression model / Four-predictor in fourth turn

	System		
Predictors	Estimate	Statistic	**p-value**
(Intercept)	0.76	-0.18	**0.861**
Step Time	1027.40	0.67	**0.500**
Stance Time	25.12	0.47	**0.641**
Swing Time	0.00	-0.96	**0.336**
DS Time	0.00	-1.16	**0.245**
Observations	36		

A decrease in two out of three p-values of the predictors (step time and swing time) in the model is shown from the result (Table 7) after entering the double support time to the model compared to the previous step. However, the insignificancy of all four predictors relative to the system type is obtained, which again confirms no meaningful difference between Mocap and OpenPose. The results are rounded up to 2-digits.

Next, step length is added to the model as predictor.

Table 8) Results of Logistic regression model / Five-predictor in fifth turn

	System		
Predictors	Estimate	Statistic	**p-value**
(Intercept)	0.75	-0.19	**0.851**
Step time	21916.24	0.78	**0.434**
Stance time	31107	0.16	**0.870**
Swing time	0.00	-0.99	**0.322**
DS time	0.00	-0.88	**0.380**
Step Length	4.96	0.41	**0.679**
Observations	*36*		

Having five independent variables in the fitted model, shows high p-value for two of them (stance time and step length) and moderate level for the other three (Table 8). The evidence approves that the null hypothesis is accepted again. The results are rounded up to 2-digits.

In the last run of the fitting model, the predictor step width is inserted.

Table 9) Results of Logistic regression model / Six-predictor in sixth turn

	System		
Predictors	Estimate	Statistic	**p-value**
(Intercept)	235200.03	16469	**0.014***
Step time	811555555.50	45658	**0.212**
Stance time	0.09	-0.23	**0.814**
Swing time	0.00	-1.87	**0.062**
DS time	4.95	0.09	**0.926**
Step Length	5.59	0.37	**0.709**

Step width	0.00	-2.76	**0.006***
Observations	*36*		

Opposing the previous steps, a significant p-value (0.006) is showed up referring to adding the predictor step width in the model (Table 9). It represents that there is an association between the step width and the type of system such that step width is different for each level of system type meaning that it has a significant relationship with the system type. The same result for this variable was obtained in the correlation analysis part also.

Except step width, all other five independent variables are still confirming that there is no relationship between them and the system type.

The forward approach and the complete model are in line considering hypothesis testing results. From the regression analysis results step time, stance time, swing time, DS time and step length proved to be insignificant in the relationship with the system type. For further clarification the above mentioned independent variables have no statistically significant effect on system type. Also, the only significant independent variable is step width which the p-value resulting from the test is relatively less than 0.05.

4.1.4 PLS-DA

To assess the ability of the pose tracking algorithm (OpenPose) in differentiating the measured types of gait, Partial Least-Squares Discriminant Analysis (PLS-DA) is performed. PLS-DA is a machine learning tool that is being used increasingly as feature selector and classifier. It is a combination of principal component and regression analyses to extract key features by modeling covariance structures.

As a linear, multivariate model, PLS-DA, use the partial least square (PLS) algorithm to classifies the labelled data by finding the components that best separate the sample groups (Ruiz-Perez, et al., 2020) (Zhou, et al., 2020). It has well performance for the data with multiple independent variables and lower number of observations (Eriksson, et al., 2006), which is present in the case of this study.

In the PLS analysis the main goal is to define a maximum covariance model and explain the relationship between the gait variables (predictors) and system type, OP and MC (responses). To this end, successive orthogonal factors are selected that maximize the covariance between each predictor and the corresponding response to find a model that best assign the system type with a selected number of gait variables.

The input data in performing the PLS-DA analysis, consists of the gait variables (predictors) which formed the X-matrix, and the system type (response) as the Y-matrix; For the discriminant analysis, the observations separated to five groups according to the five different type of walking pose namely normal, slow, short, wide, and limp. Gait variables include step time, stance time, swing time, double support time, step length and step width. The PLS-DA model is constructed using R software. In the model two principal components (comp1 and comp2) are considered. It classifies the two samples of measuring systems (OP and MC) into known groups of gait type (normal, slow, short, wide, and limp) by finding patterns and relations between all the extracted gait parameters, test conditions, and measuring systems. The result of the model is visualized as shown in the Figure *9*.

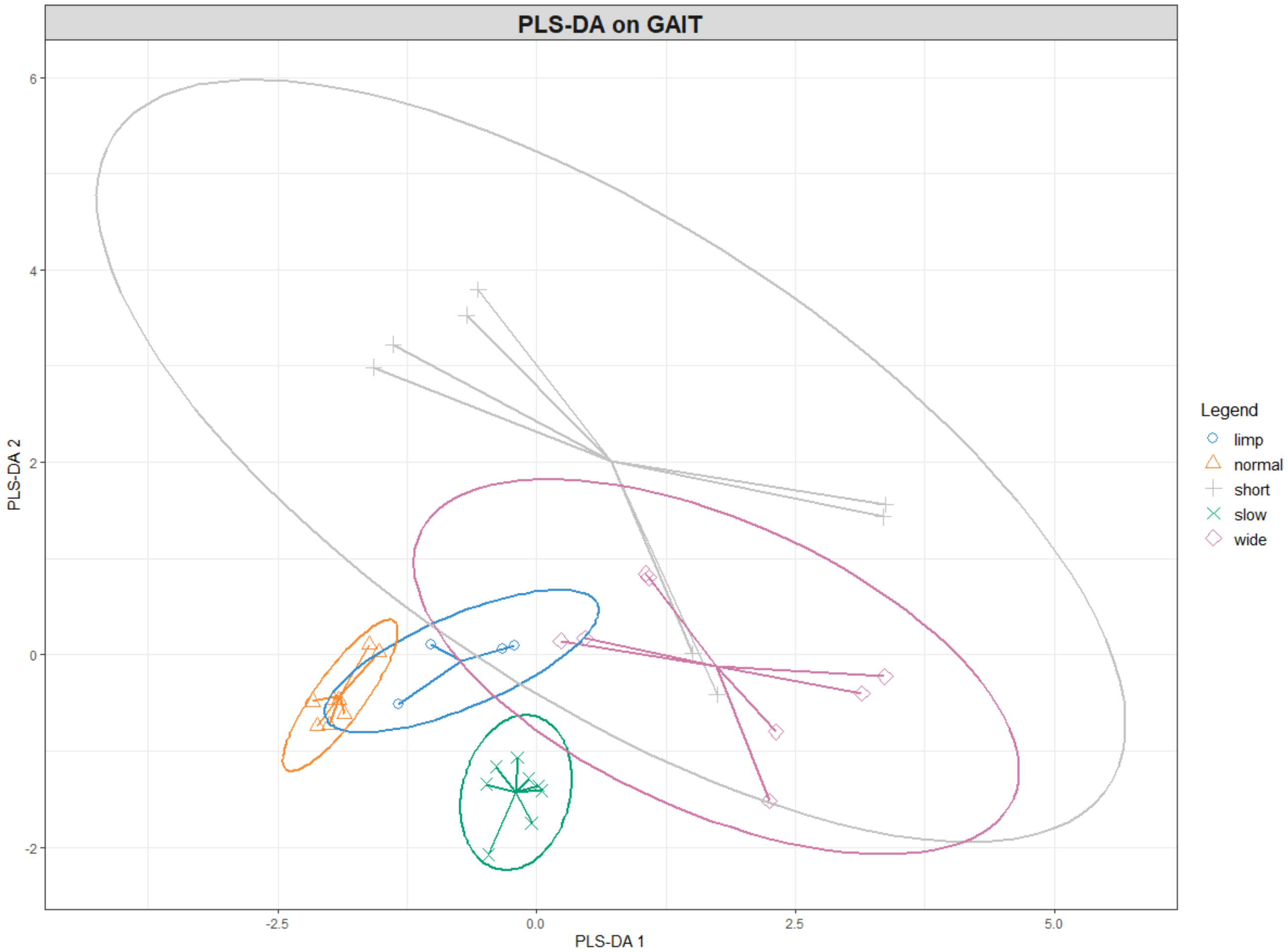

Figure 9)Star plot of PLS-DA clusters, different gait types are shown in different colors, x-axis shows the first component and the y-axis represents the second component

This star plot considering the observations from both measuring systems together and shows the clustering of each sample according to the gait type by different colors, the arrows from each group shows centroid towards each individual sample, the confidence ellipses are plotted for each sample and the confidence level set to 95%. Some discrimination can be seen between the slow gait and wide gait samples vs. the others on the first component (x-axis), and normal, limp, and short gait vs. the others on the second component (y-axis).

To show how the observations measured by each system is located in the gait-type-based clusters another visualization of the PLS-DA with the detailed of system type (OP and MC) is presented.

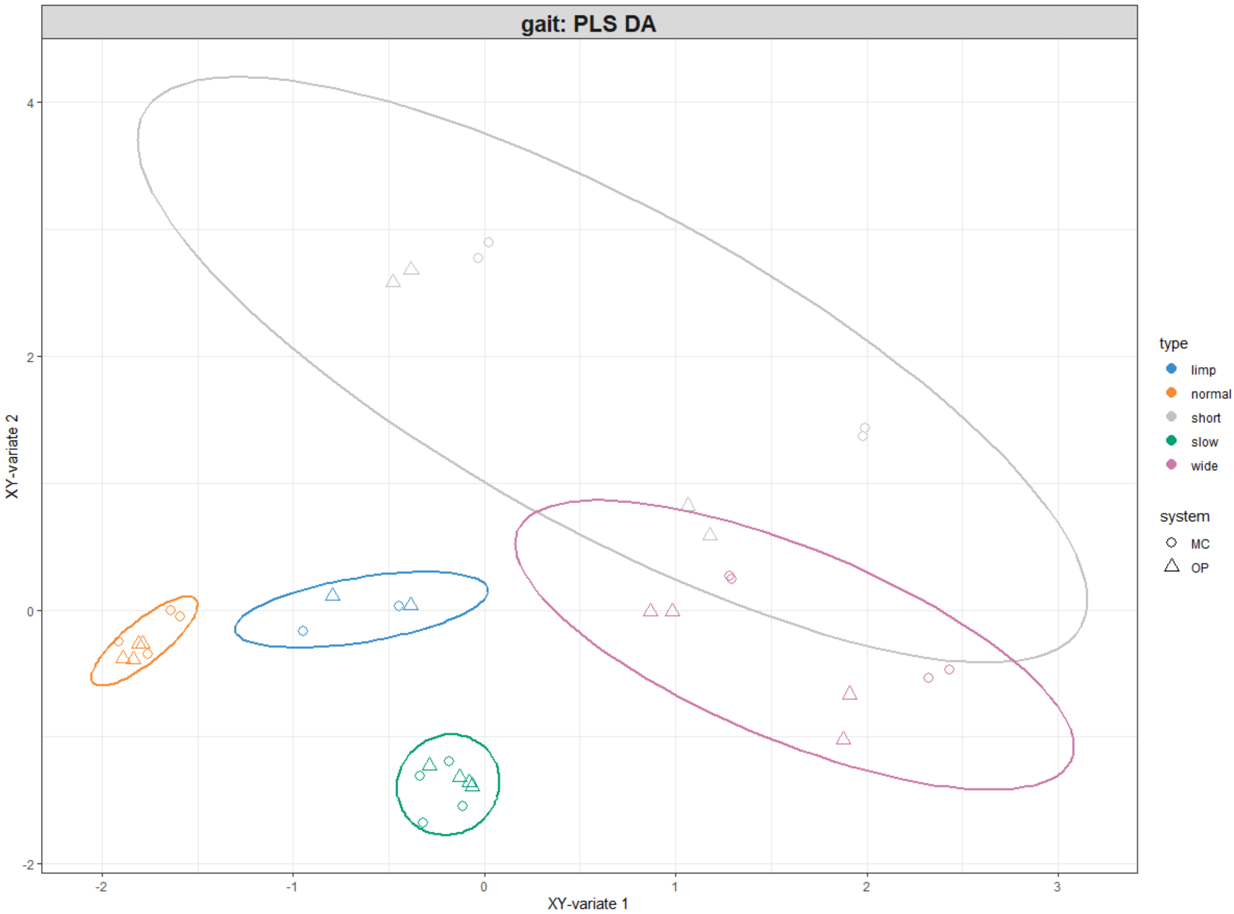

Figure 10) PLSDA plot showing clusters of different gait types in different colors, x-axis shows the first component, and the y-axis represents the second component, MC refers to motion capture, and OP means OpenPose

The distinction shown in the above graph represents that the PLSDA model differentiates between different types of gait including normal, slow, short, wide, and limp in both

Motion capture and OpenPose in similar clusters and shows no major differences between MC and OP measure-methods.

4.2 Balance results

By visualizing 2D displacement of CoM from Open Pose data and CoM from 3D Motion Capture data for all balance tests (three normal balance tests and one abnormal balance test) in line graphs, a well agreement between both systems is observed(Figure *11*,Figure *12*,Figure *13*,Figure *14*). To verify the visual results statistical testing is performed in next part.

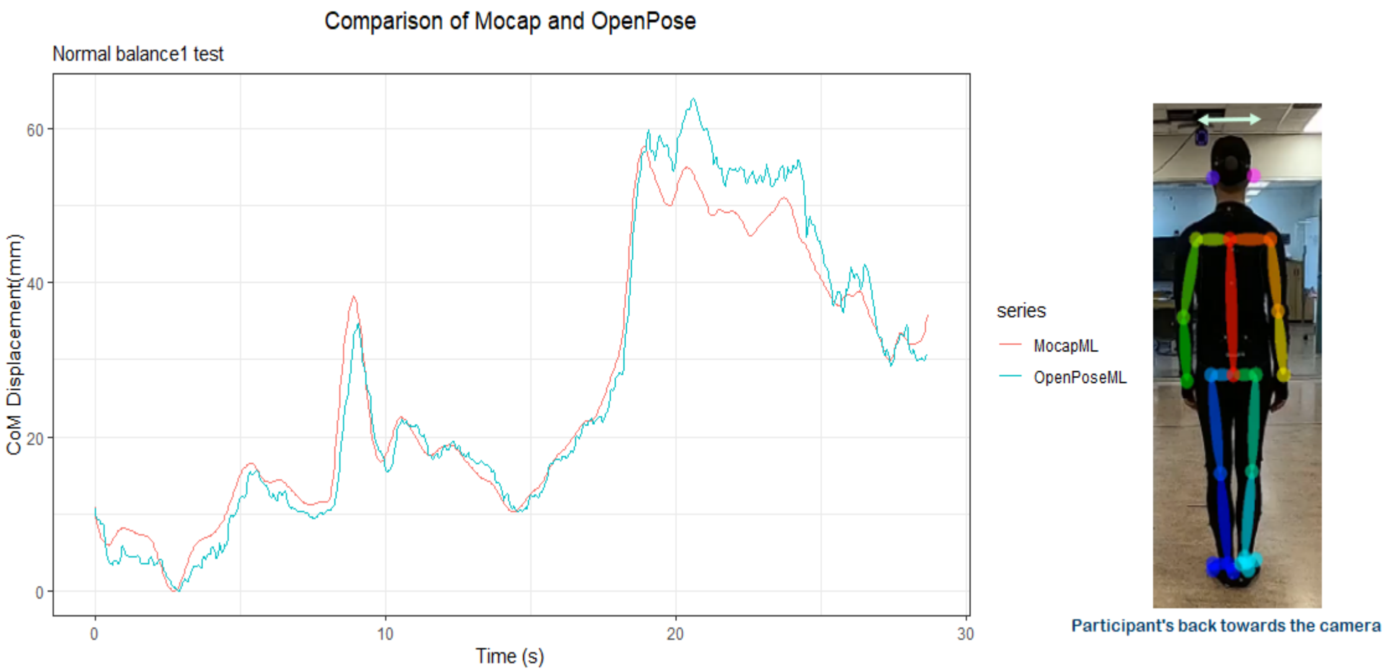

Figure 11) CoM displacement(mm) during the normal balance test 1(30 s), participant's back towards camera, from OpenPose and Motion capture

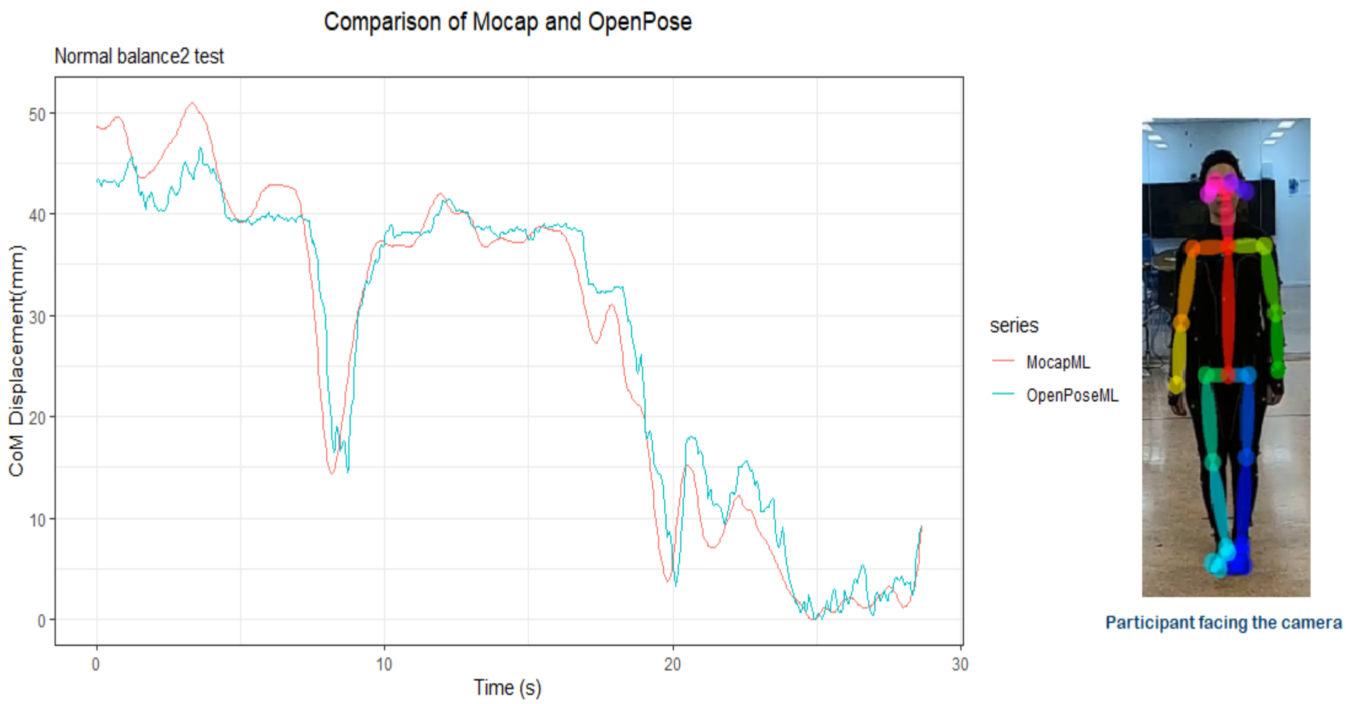

Figure 12) CoM displacement(mm) during the normal balance test 2(30 s), participant facing camera, from OpenPose and Motion capture

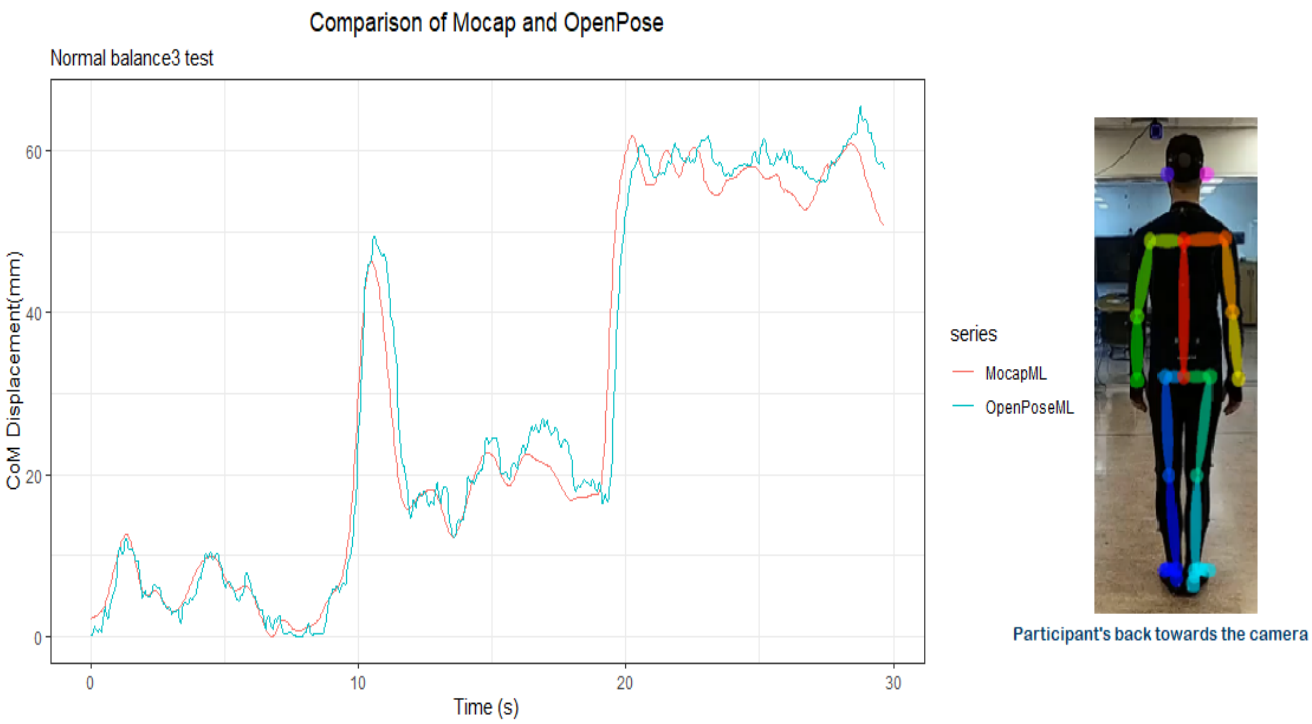

Figure 13) CoM displacement(mm) during the normal balance test 3 (30 s), participant's back towards camera, from OpenPose and Motion capture

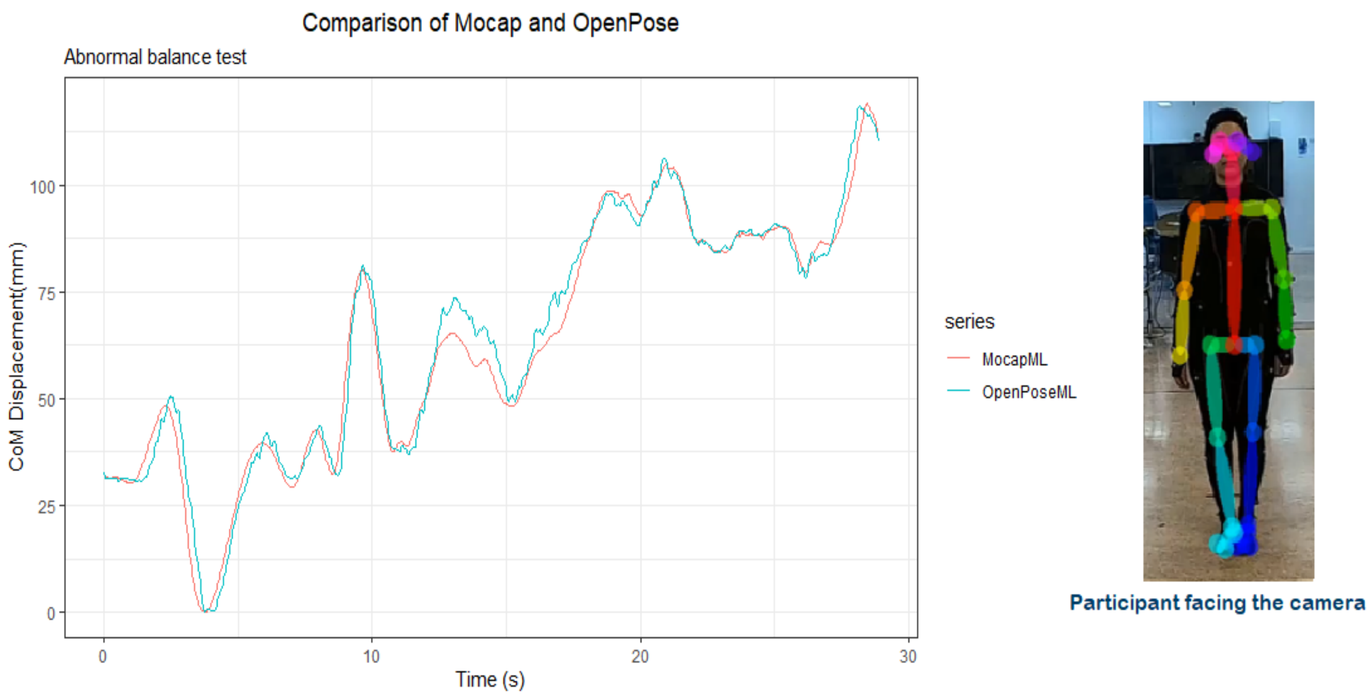

Figure 14) CoM displacement(mm) during the abnormal balance test (30 s), participant facing camera, from OpenPose and Motion capture

To compare two groups of CoM data provided from the recordings of Mocap and OpenPose, the means of two samples are tested against each other. For applying the proper test to the case of this study, among the two-sample hypothesis tests, the normality of the data is investigated. Since the size of the balance dataset is large, the Jarque–Bera test is considered to verify if the data are normally distributed or not.

Referring to the Jarque–Bera test, normality of data considered as the null hypotheses and reverse is settled at the alternative hypothesis. According to the test result, the obtained p-value is close to zero, therefore the null hypothesis is rejected. Due to the non-normality of data, the unpaired two-samples Wilcoxon test which is a non-parametric alternative to the unpaired two-samples t-test is performed to compare two groups of CoM data from OpenPose and Mocap.

For each of the tests p-value is calculated using R software. The results are shown in The attained p-value in the first trial of balance test (Normal balance1 test), equals to 0.97 which is strongly insignificant and toward accepting the null hypothesis and shows that mean level of both samples is the same. In the two other balance trials and also in abnormal balance trial, p-value shows insignificant values, confirming that both Mocap and OpenPose are in well agreement with each other.

Table *10*. The attained p-value in the first trial of balance test (Normal balance1 test), equals to 0.97 which is strongly insignificant and toward accepting the null hypothesis and shows that mean level of both samples is the same. In the two other balance trials and also in abnormal balance trial, p-value shows insignificant values, confirming that both Mocap and OpenPose are in well agreement with each other.

Table 10) Results from two-group comparison test driven from CoM values between Mocap and OpenPose in four different balance trials (Normal balance 1, Normal balance 2, Normal balance 3 and Abnormal balance)

Two-sample test result of Normal balance1 trial, Observations: 860

statistic	parameter	p.value	null.value
c(W = 370238)	NULL	0.966116422618461	c(`location shift` = 0)

alternative	method	data.name
two.sided	Wilcoxon rank sum test with continuity correction	balance_normal1$MocapML and balance_normal1$OpenPoseML

Two-sample test result of Normal balance2 trial, Observations: 859

statistic	parameter	p.value	null.value
c(W = 362853)	NULL	0.553813056705968	c(`location shift` = 0)

alternative	method	data.name
two.sided	Wilcoxon rank sum test with continuity correction	balance_normal2$MocapML and balance_normal2$OpenPoseML

Two-sample test result of Normal balance3 trial, Observations: 890

statistic	parameter	p.value	null.value
c(W = 375882)	NULL	0.0628808130753406	c(`location shift` = 0)

alternative	method	data.name
two.sided	Wilcoxon rank sum test with continuity correction	balance_normal3$MocapML and balance_normal3$OpenPoseML

Two-sample test result of Abnormal balance trial, Observations: 867

statistic	parameter	p.value	null.value
c(W = 369752)	NULL	0.558977046142333	c(`location shift` = 0)

alternative	method	data.name
two.sided	Wilcoxon rank sum test with continuity correction	balance_abnormal$MocapML and balance_abnormal$OpenPoseML

Chapter 5

5. Discussion

We examined the performance of pose estimation (OpenPose) in detecting different types of postures both for walking (normal, slow, wide, limp, and short walking types) and balance experiments (normal and abnormal balance) by comparing the quantitative 2D spatiotemporal gait measurements against a golden standard. The comparisons were performed for videos captured by front and right-side cameras.

Results from our research indicate that five out of six gait parameters namely the step time, stance time, and double support time measures calculated from the OpenPose correlate significantly to that of the motion capture system. However, the step width is the only parameter that designates a low correlation between them. Similarly, the results from logistic regression modeling showed insignificant relationship between these five gait parameters and the two pose capturing tools (Mocap and Openpose), while step width represented a relatively significant effect on them. It might be due to the effect of frontal plane video perspective on the scaling of pixels to meters, since the values obtained from the pose estimation are dimensionless and cannot be directly compared with motion capture values; This conversion of pixels to meters introduced error. The PLS-DA model (Partial Least Square Discriminant Analysis) demonstrated that gait variables extracted from OpenPose and Motion capture can be discriminated in clusters based on gait type with no major differences between OpenPose and Mocap. Also, the results from a two-group comparison test (Wilcoxon) on balance parameter (CoM values) between Mocap and OpenPose showed that the mean level of both samples is the same in four different balance trials, including three balance trials and one imbalanced experiment.

Overall, the results suggest that pose estimation showed promising performance in discriminating among normal and abnormal poses as compared to the golden standard (Mocap) in both walking and gait experiments.

The findings of this study are in line with the recent studies using OpenPose in terms of its robustness for two-dimensional analysis of human pose (Cao, et al., 2019) (Chen, 2019) (Kim, et al., 2021) (Li, et al., 2021) (Mehdizadeh, et al., 2021) (Stenum, et al., 2021), which could be considered as the next achievement to the chain of forward research in human movement context. While gait and balance are among key human movement to be assessed in ergonomics research using pose estimation, other common occupational postures in different workplaces can be considered in future studies.

Using wearable sensor-based tools vs video pose estimation for human postural analysis is a controversial issue. This is a discussion among researchers, ergonomists, workers, employers, and clinicians, with advantages and disadvantages on both sides (sensors vs video pose estimation). On one hand, video pose estimation might allow activity assessment without placing sensors on people and might be cheaper if it can be done with conventional video cameras. On the other hand, there is the issue of privacy, data security, and monitoring, where video data is significantly more sensitive than data from movement sensors. To sum up, it depends a lot on the final application, and the availability of resources for safe and ethical data management if video is to be collected on regular basis at the workplace.

Furthermore, the limited dataset of our work due to the performed preliminary experimental research could be considered for future studies, which suggests the need for a more systematic data collection protocol that could also aid in improving data quality and facilitating the acquisition of larger datasets.

In experimental aspect, estimation of step lengths and widths with pose estimation is influenced by the position of the participant along the field of view of the camera. To generate estimates of spatial gait parameters (e.g., gait speed, step length) it is necessary to scale the video. Here, we accomplished this by scaling the video to known measurements on the ground. The process for scaling frontal plane video requires additional linear interpolation to account for changes in the distance to the field of progression during gait (participant walking away or towards the camera is seen in pose estimation as a change in height in screen coordinates).

Although stationary camera recordings for sagittal plane with consistent camera height gave the best results. Frontal plane video results could be improved if the camera follows the participant at a fixed distance and with minimal height changes. The developed framework relies on several post-processing steps, some of which were completed manually. This includes detection of multiple persons, left-right limb switching and gaps in the data.

We anticipate that clinical video-based analyses will be performed on videos taken by smartphone, tablets, or other household electronic devices. Many of these devices have standard frame rates of 30 Hz during video recording are comparable to the ones used in this study.

We did not directly compare the results of our pose estimation analyses to results of any other markerless approaches (e.g., Kinect), nor did we run a comparison with other available pose estimation algorithms (DeepPose, DeepLabCut, OpenPifPaf).

Pose estimation methods do not track movements of the human body perfectly from frame-to-frame. The body key points are unlikely to be equivalent to the marker landmarks as they rely on visually labeled generalized points (e.g., “ankle”, “knee”) whereas motion capture marker placement relies on manual palpation of bony landmarks. Pose estimation methods are also capable of three-dimensional human movement analysis through multiple simultaneous camera recordings.

Here, we assumed that most videos taken in the home or clinic will be recorded by a single device, thus, we limited this study to two dimensional analyses of human walking and balance. We used a pre-trained network provided by Open-Pose to avoid spending time and resources training our own network. However, it may be possible to obtain more accurate video-based analyses by training gait- and balance-specific networks from different views (e.g., sagittal, frontal) and for different movement conditions.

Chapter 6

6. Conclusion and future work

This study provides preliminary evidence that pose estimation (using OpenPose) could work as a tool for quantitative 2D spatiotemporal analyses of gait and balance as the key human movements to be referred in ergonomics postural assessment. Pose estimation (OpenPose) were compared to a golden standard (Mocap) through a set of physical pose-based tests. The experiments were two-fold: Gait trials that were tested under five different status including normal, slow, short, wide, and limp, and balance posture which were examined on normal and abnormal positions. Overall, the results suggest that pose estimation showed promising performance in discriminating among normal and abnormal poses as compared to the golden standard (Mocap) in both experiments. Besides the results show that gait and balance analysis through pose estimation could detect changes across conditions. Therefore, this reveals the potential for three-dimensional pose estimation using multicamera setups in future researches.

However, the same results from the two performed statistical tests namely correlation analysis and logistic regression were obtained in the gait parameters measurements; It represented that although pose estimation showed agreement with the golden standard (Mocap) in measuring step time, stance time, double support time and step length, it demonstrated relatively poor performance in estimating step width. It might be due to the effect of frontal plane video perspective on the scaling of pixels to meters. Hence, future studies should be engaged in developing and validating a more precise pose estimation from frontal views.

Furthermore, the limited dataset of our work due to the performed preliminary experimental research could be considered for future studies, which suggests the need for a more systematic data collection protocol that could also aid in improving data quality and facilitating the acquisition of larger datasets.

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1. ABSTRACT

Background: Taking into consideration the vital role of postural evaluation in ergonomics within logistics, examining pose estimation as the state-of-the-art in human movement studies is targeted to be addressed in this research. The goal of this study is to experiment with OpenPose as a popular open-source pose estimation algorithm to analyze the quantitative 2D spatiotemporal gait and balance. In most recent studies on pose estimation, only a single posture at a time has been examined. However, this study focuses on examining the performance of pose estimation (OpenPose) in detecting different types of postures both for walking (normal, slow, wide, limp, and short walking types) and balance experiments (normal and abnormal balance) by comparing the quantitative 2D spatiotemporal gait and balance measurements against a golden standard.

Method: We compared recordings of quantitative gait parameters in 24 walking trails and center of mass (CoM) displacement in 6 balance tests tracked from OpenPose and Motion capture which were performed by two participants. The comparisons were performed for videos captured by front and right-side cameras.

Results: The same results from two of the performed statistical tests namely correlation analysis and logistic regression were obtained in the gait parameters measurements; It represented that pose estimation showed agreement with the golden standard (Mocap) in measuring step time, stance time, double support time and step length, and only in estimating step width it demonstrated relatively poor performance. The PLS-DA model (Partial Least Square Discriminant Analysis) demonstrated that gait variables can be discriminated in clusters based on gait type with no major differences between OpenPose and Mocap. Also, the results from a two-group comparison test (Wilcoxon) on balance parameter (CoM values) between Mocap and OpenPose showed that the mean level of both samples is the same in four different balance trials, including three balance trials and one imbalanced experiment.

Conclusion: This study provides preliminary evidence that pose estimation (using OpenPose) could work as a tool for quantitative 2D spatiotemporal analyses of gait and balance as the key human movements to be referred to in ergonomics postural assessment.

The results suggest that pose estimation showed promising performance in discriminating among normal and abnormal postures as compared to the golden standard (Mocap) in gait

and balance experiments. This reveals the potential for three-dimensional pose estimation using multicamera setups in future research.

Keywords: Ergonomics Logistics, pose estimation, Openpose, human movement

2. INTRODUCTION

Nowadays an integral part of supply chain management is to meet the demanding need of the business world to maximize yield while minimizing costs and achieving the highest possible quality. Achieving agility, high productivity, and high quality entails competitive excellence in supply chain management. The strength of the supply chain depends upon, among other things, the amount of operation's output which is affected by a bunch of factors including the human factor as a significant driving force.

Ergonomics plays a vital role in supporting the efficiency and productivity of supply chain operations by maintaining the relationship between the company and the environmental aspects (Markus, 2008). A good workplace ergonomic system allows employees to operate at their highest level of productivity, quality, and efficiency.

Workplace ergonomics' importance arises mainly from the risk factors that can threaten both the worker's health and the operation output which may be quite costly to both the employee and employer. An ergonomic approach can contribute to lower business costs, improved quality, and better workplace safety. The evaluation of workplaces ergonomics investigates the risks of the physical interaction of people with their work environment which is settled in three areas including kinesiology (the study of human movement), biomechanics (the study of motion in living things), and the relation of kinesiology and biomechanics with workplace safety (Hazari, et al., 2021).

Human movement and posture are two main factors that are considered in the evaluation of ergonomics. There are several observational methods of postural ergonomics assessment based on direct on-site observation or the video of workers when performing their jobs (Hignett & McAtamney, 2000) (Diego-Mas, et al., 2015) (Kee, 2021).

With the emergence of computer vision, vision-based approaches are making an outstanding headway for marker-less postural assessment as they provide the assessment availability from photos and videos captured by standard cameras (Bogo et al., 2016; Cao et al., 2017; Mehta et al., 2017; Rhodin et al., 2018; Yang et al., 2018; Zhou et al., 2017). While the vision-based methods used in ergonomics research mainly focused on identifying major key points of the human body, in a recent study the joint angles were computed using OpenPose (Kim, et al., 2021). However, the results of studies on the investigation of human kinematics considering the ergonomics context have yet to achieve a reliable level of accuracy.

In this study, the application of OpenPoes for assessing human balance, kinematics, and spatiotemporal analysis of gait are presented. The difference of this research from the limited prior counterparts (Kim, et al., 2021) (Stenum, et al., 2021) (Li, et al., 2021)is twofold; This study has examined the pose estimation (OpenPose) robustness, first, in discriminating between the different types of walking, second, in detecting the balanced and imbalanced postures, compared to the measurement simultaneously derived from a golden standard.

3. LITERATURE REVIEW

The necessity of appointing the relationship between logistics and human, organizational, and social traits originates from the concept of logistics which involves people, materials, information, equipment, energy resources, as well as related knowledge and abilities, and can make satisfactory results (Loos, et al., 2016).

The extremely routine and manual nature of logistical activities may put employees at high risk of physical strain in working environment which entail gaining empirical insights into examining ergonomics within logistics (Gruchmann, et al., 2020). Manual labors in logistics workplace settings including warehouses and distribution centers mostly consist of repetitive physical movements throughout the day, such as twisting, lifting, bending, or sitting in an awkward position which expose the workers to overexertion, pain, and musculoskeletal disorders (Schmauder, 2013) (Günthner, et al., 2014). For instance, “100 million European citizens suffer from chronic musculoskeletal pain and musculoskeletal disorders (MSDs), including 40 million workers who attribute their MSD directly to their work” (Hartvigsen, et al., 2018).

The ergonomic assessment used to be done through observing the operators during work by the experts which were time consuming and required specialized ergonomists (Grooten & Johanssons, 2017). Today with the transition to Industry 4.0 and the introduction of new digital technology, monitoring of workers' physical and psychological well-being is supported through integrated platforms (Kadir & Broberg, 2020). There are two popular devices for ergonomics assessment in workplaces namely Inertial Measurement Units (IMU) which is among the wearable-sensor based tools and Microsoft Kinect as a vision-based tool (Tee, et al., 2017). Rocha-Ibarra et al. evaluated human ergonomics of a pick and place task using the Microsoft Kinect™ sensor to capture the postures of the subjects (Rocha-Ibarra, et al., 2021). Fledmann et al. examined the ergonomic evaluation of body postures in the logistical activities of order picking systems by using a motion capturing system (Feldmann, et al., 2019).

The worker motion data for developing the concept of a Healthy Operator 4.0 (HO4.0) proposed by Sun et al. was collected through wearable devices (Sun, et al., 2020).

In several studies for the real-time monitoring of an operator's activities wearable technologies were used (Kassner, et al., 2017) (Romero, et al., 2017) (Pavón, et al., 2018).

Other studies presented the use of deep learning to monitor an operator's activities utilizing wearable devices for data collection (Zheng, et al., 2018) (Shoaib, et al., 2016). For the ergonomic assessment of physical workload, Onofrejova et al. used sensor-based wearable technologies and highlighted the ergonomic risk in industrial environment (Onofrejova, et al., 2022). Another research addressed a variety of sensor-based wearable stretch sensors for human movement monitoring within workplace practices in physical ergonomics (Chander, et al., 2020). By using smart wearable devices Ciccarelli et al. provided a human work sustainability tool which consider all work-related ergonomic aspects including physical, cognitive, environmental, and organizational (Ciccarelli, et al., 2022). Seo & Lee proposed a 2D image-based approach that automatically classify workers' postures by using machine-learning algorithms which addressed the automating current postural ergonomic evaluation techniques (Seo & Lee, 2021). Moreover, in another study a combination of computer vision approaches, and wearable sensors utilized to improve the accuracy of ergonomic risk detection as well as workers' locations (Yu, et al., 2019). To sum up, to date ergonomic assessment is performed through two categories of technologies including body-attached sensor-based approaches and vision-based approaches.

While the researchers mainly used the wearable sensor-based methods in ergonomic assessment, limited researches have addressed the vision-based methods (Kim, et al., 2021). Recognizing posture through devices connected to the body can be named as the main drawback of motion capturing wearable tools because they limit the type of motion recording at each trial as well as their requirement of specific settings. Moreover, the 2D image-based approach limitation refers to collecting dataset due to its requirement to large training data set, as a machine learning-based classification method (Yan, et al., 2017).

Human pose estimation as an emerging technology that measures human movement kinematics can be addressed these limitations by using only standard camera videos (Cao, et al., 2017) (Zago, et al., 2020) (Viswakumar, et al., 2019) (Kidziński, et al., 2020) (Sato, et al., 2019) (Fang, et al., 2017) (Mehdizadeh, et al., 2021) and freely available packages of training datasets (Stenum, et al., 2021). Using a simple regular camera to capture the whole-body kinematics could considerably lessen the role of common techniques which are limited in terms of cost, technical expertise requirements, and obtrusiveness such as motion capture systems or wearable devices. In a prior study, a pose estimation-based method (OpenPose) has been used for ergonomic postural assessment by measuring joint angles which is also validated against a reference Xsens inertial MoCap system (Kim, et al., 2021).

To sum up, while measuring the logistics ergonomics factors which are essential for ergonomics assessment are mainly performed through wearable sensor-based devices lately, the vision-based methods which required only standard camera to capture human pose are progressing today with the potential to use in the logistics ergonomics. According to the literature (Kim, et al., 2021) (Li, et al., 2021) (Stenum, et al., 2021), addressing the robustness of pose estimation algorithms as the latest up-to-date methods for two-dimensional analysis of human pose, is needed to add the next achievement to the chain of forward research in logistics ergonomics context. OpenPose as an opensource pose estimation algorithm has been studied on several objectives in recent years (Cao, et al., 2019) (Chen, 2019) (Kim, et al., 2021) (Li, et al., 2021); The findings represented the pose estimation application in detecting body points and angle joints in ergonomics researches as well as human balance and human kinematics and spatiotemporal gait in clinical settings when the experiments are designed for investigating one type of posture. However, this study focuses on analyzing the performance of pose estimation (OpenPose) in detecting different types of postures both for walking and balance experiments.

4. METHODS and DATA

The study is conducted at the laboratory of SINTEF Digital, a research division in SINTEF, located in Trondheim, at the Department of Mathematics and Cybernetics, to assess the estimation of standard clinical gait parameters such as step length, step width, swing time, step time, stance time and double support time as well as center of mass displacement as a balance parameter with the use of pose estimation methods.

Data collecting were performed through two experiments, walking trials and balance tests. In walking experiment totally, 36 records from 12 walking trials in two directions captured from pose estimation (OpenPose) and Mocap. The walking measures got from averaging over the steps of each participant.

For the balance experiment, four datasets from different 30-seconds balance trials were provided, each consists of more than 850 observations derived from the videos of both OpenPose and Mocap.

4.1 Participants

Due to the different gait and balance types as the aiming of data collecting for the experiments of this study, two participants were contributed who were asked to simulate the defined postures according to the protocol of the study. Each participant performed five different types of walking and two different types of balance trials. They agreed to be videotaped during the data collection period as an element of the study.

4.2 Motion capture system

Measurements of optical motion capture have long been regarded as one of the gold standards in the field of biomechanics within the research community. Regarding the validity of optical motion capture systems Yeo et al. suggested Qualisys for efficient and accurate measurements of gait analysis. In this study three-dimensional (3D) motion capture Qualisys with six cameras (Figure 1) was used to capture participants' motion at 200 Hz while they were wearing whole-body markers (with 39 markers). Qualisys QTM software was used to record and pre-process the walking trials.

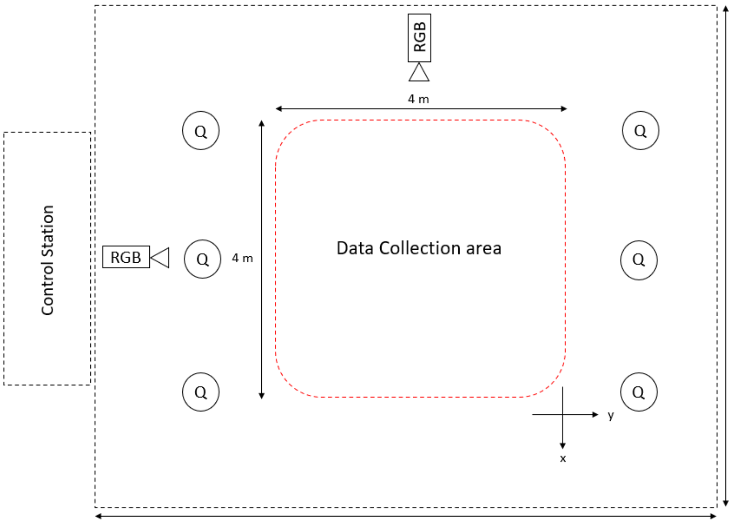

Figure 15 : Laboratory setting, **Q** Qualisys cameras, **RGB** GoPro cameras

4.3 Cameras

With the aim of using regular video cameras in pose estimation, two Go Pro Hero cameras were used to record video from sagittal and frontal views at 60Hz with a 1080p resolution. The cameras were placed centered and outside of the 4x4 meter recording space (Figure 1), for footage from front and right side.

From both walking trials and balance tests, 30 videos from each of the front and right-side cameras including 12 walking trials in two directions and four balance test trials were obtained. Likewise, 30 motion capture recordings were captured with the same performed experiment.

4.4 Experimental protocol

For assessing pose estimation in a standard clinical setting, as the suggestion of several physiotherapists who got involved in this study, SPPB test was conducted for providing the reference metrics to be compared between 2D video-based pose estimation algorithms and 3D golden standard motion capture system. Participants were asked to complete two tasks of SPPB test: assessment of standing balance and 4-m walking back and forth per trial. Laboratory settings are shown in (Figure 1).

Following the SPPB protocol, it was determined that several simulated gait and balance types be performed by each participant. These motion tasks included normal and disturbed balance tests as well as normal and several abnormal gait trials. Walking slow, short, wide, and limp comprised the performances in simulating the abnormal gait tests. In total 18 records in walking trials were captured by both instruments (3D Mocap and 2D video-based cameras) simultaneously.

The standing balance test was performed in three phases; First, participants were asked to remain standing with their feet as close together as possible, second, in a semi-tandem position, and finally in a tandem position. Each position had to be held for 10 s.

One 30-seconds abnormal balance test simulated by each participant and three normal balance tests performed which were recorded concurrently by Motion capture and Gopro cameras. By extracting the displacement of COM from the recordings, four different datasets each consists of more than 850 observations per system provided.

4.5 Video pose estimation (Data processing)

Data pre-processing involved labelling and gap-filling of motion capture recordings for all trials and clipping and pose estimation processing for all video recordings. Video clipping was done to extract individual 4m walk trials from first to last step on each direction (away from frontal plane camera, and towards frontal plane camera). The recorded videos from frontal and sagittal views were processed using Open Pose in a Python script on Google Collaborative. Scripts used to process video data were developed and used by (Stenum, et al., 2021) and are freely available at https://github.com/janstenum/GaitAnalysis-PoseEstimation. Motion capture was processed in MATLAB (Mathworks 2021) to extract spatiotemporal gait metrics from 3D marker data. For motion capture and the left views of OpenPose, timings of gait events (heel-strikes and toe-offs), as well as spatiotemporal gait metrics (step time, stance time, swing time, double support time, step length, and gait speed) were separately determined.

4.6 Gait and balance parameters

Gait and balance parameters were calculated using the recorded gait and balance from 3D Mocap Qualysis and 2D records from Openpose. The calculated gait variables include Step time (duration in seconds between consecutive bilateral heel-strikes), Stance time(duration in seconds between heel-strike and toe-off of the same leg), Swing time (duration in seconds between toe-off and heel-strike of the same leg), Double support time (duration in seconds between heel-strike of one leg and toe-off of the contralateral leg) and Step length (anterior-posterior distance in meters between left and right ankle markers (motion capture) or ankle key points (OpenPose) at heel-strike), Step width(medial-lateral distance in meters between left and right ankle markers (motion capture) or ankle key points (OpenPose) at heel-strike) and Gait speed(step length divided by step time).

Analysis of the balance test was done through the trajectory of the Center of Mass (CoM). CoM was estimated with the segmental kinematics method (Winter, 1990), where inertial parameters of body segments allow the computation of the body center of mass through the weighted average of the CoM of each segment. Anthropometric data, including the mass distribution within the segments and the location of their CoM, were taken from (Wiley & Sons, 1990). Processing of motion capture data and estimation of CoM trajectory was done in custom-made Python scripts. Processing of video and pose estimation data was done using a customized version of the tools described in (Stenum, et al., 2021) and custom-made MATLAB scripts.

4.7 Statistical analysis

4.7.1 Gait analysis

Analysis of the gait in this study is done in four parts. First, an overall view of the gait data from Motion capture and OpenPose is described shortly, the results are reported in descriptive analysis section.

Then, correlation analysis is used to determine the correlation between the gait variables calculated from the video and from the motion capture system as the golden standard, the results are reported in correlation analysis section.

In the next part, logistic regression is used for comparing the estimation of gait parameters (step time, stance time, swing time, double support time, step length, and step width) between the gold standard motion capture and pose estimation. For that, logistic regression modeling is developed in several stages. Logistic Regression is from a family of generalized linear models (GLM). It is a binary classification algorithm used when the response variable is binary (1 or 0) which includes dependent variables that are non-normal. This method without considering the normality assumption for the predictor variables, predict the values of response variable (David W. Hosmer, et al., 2013). We used it to find the best fitting and clinically interpretable model to describe the relationship between the type of system (Mocap or OpenPose) and all six numeric gait parameters (step time, stance time, swing time, double support time, step length, and step width) (David W. Hosmer, et al., 2013).

The system type (Mocap or OpenPose) is considered as the dependent (response) binary variable and six gait parameters are defined as independent variables in the model. For this purpose, the family argument in GLM function is set to **binomial()** .In a GLM model a coefficient is assigned to each independent variable and the model is written as below:

$$system.type = \beta_0 + \beta_1 * step.time + \beta_2 * stance.time + \beta_3 * swing.time + \beta_4 * DS.time + \beta_5 * step.length + \beta_6 * step.width$$

In the above model the null hypothesis (H_0) and the alternative hypothesis for each independent variable (H_1) are written as follow:

$$\begin{cases} H_0 : \beta_i = 0 \\ H_1 : \beta_i \neq 0 \end{cases}, \quad i = 0, 1, \ldots, 6$$

The hypothesis $\beta_i = 0$ means that the independent variable corresponding to this coefficient is not significant in the model. In other words, the independent variable has no significant relationship with the response variable and if the p-value resulting from the GLM test is greater than the significance level (0.05) the null hypothesis is accepted. Alternative hypothesis represents that there is a statistically significant association between independent variable under study and the type of system. The results are reported in logistic regression section. Finally, for investigating the detection possibility of the pose tracking algorithm among different type of gait, PLSDA (Partial least squares discriminant analysis) technique is used.The gait measures used in the statistical analysis got from averaging over the steps of each participant. The significance level in all statistical analysis in this study is set to 0.05.

4.7.2 Balance analysis

For comparing the mean of two sample of CoM displacement which is considered as the balance parameter, hypothesis testing was performed. For that, first, to determine the appropriate type of statistical two-sample test, the test requirements including the normality test (M.Jarque & K.Bera, 1980) was checked. Then, the mean of each group is compared through Wilcoxon test. For that the null hypothesis (H_0) and the alternative hypothesis are written as follow:

$$\begin{cases} H_0 : \mu_1 = \mu_2 \\ H_1 : \mu_1 \neq \mu_2 \end{cases}$$

μ_1 refers to mean of CoM from Motion capture and μ_2 indicates mean of CoM from OpenPose in each of the defined balance tests. The results are reported in balance results section.

5. RESULTS

5.1 Gait Results

While two participants took part in the study, the experiments were designed such that each participant simulates different walking postures. Two normal and four abnormal (slow, short, wide, and limp) walking trials were performed by each participant, which formed 12 waling trials in two directions. All walking trials consisted of 4-meter walk, turn, and 4-meter walk back to starting point (2x4m walk per trial). In total, 24 videos from each of the front and right-side cameras were captured and at the same time, 24 motion capture recordings were collected. Due to different styles of walking performed in the experiment, the number of steps per trial was not identical, therefore, the values of gait parameters in each walking trial got from averaging over the steps of each participant which led to 36 records in total; This formed the reference dataset used for gait statistical analysis. The average values of the six gait measures for the motion capture (Mocap) and the pose estimation (OpenPose) are presented in Table 11.

Table 11 Gait variables values calculated for the motion capture and video data using OpenPose algorithm

Gait parameters	N	**Mean ± SD**		**Mean ± SD**	**Mean ± SD**
		MC(3D)	OP(2D)	MC - OP	|MC - OP|
Step Time (s)	36	0,71 ± 0,21	0,72 ± 0,21	0,00 ± 0,03	0,02 ± 0,02
Stance Time (s)	36	0,99 ± 0,35	0,99 ± 0,33	0,00 ± 0,05	0,04 ± 0,03
Swing Time (s)	36	0,43 ± 0,10	0,44 ± 0,10	0,00 ± 0,04	0,03 ± 0,03
Double support time (s)	36	0,28 ± 0,15	0,27 ± 0,13	0,01 ± 0,04	0,03 ± 0,03
Step Length (m)	36	0,31 ± 0,17	0,33 ± 0,17	-0,02 ± 0,07	0,04 ± 0,06
Step Width (m)	36	0,27 ± 0,08	0,21 ± 0,08	0,06 ± 0,08	0,07 ± 0,07

Snapshot of the output of walking trial from both systems is presented in Figure 2.

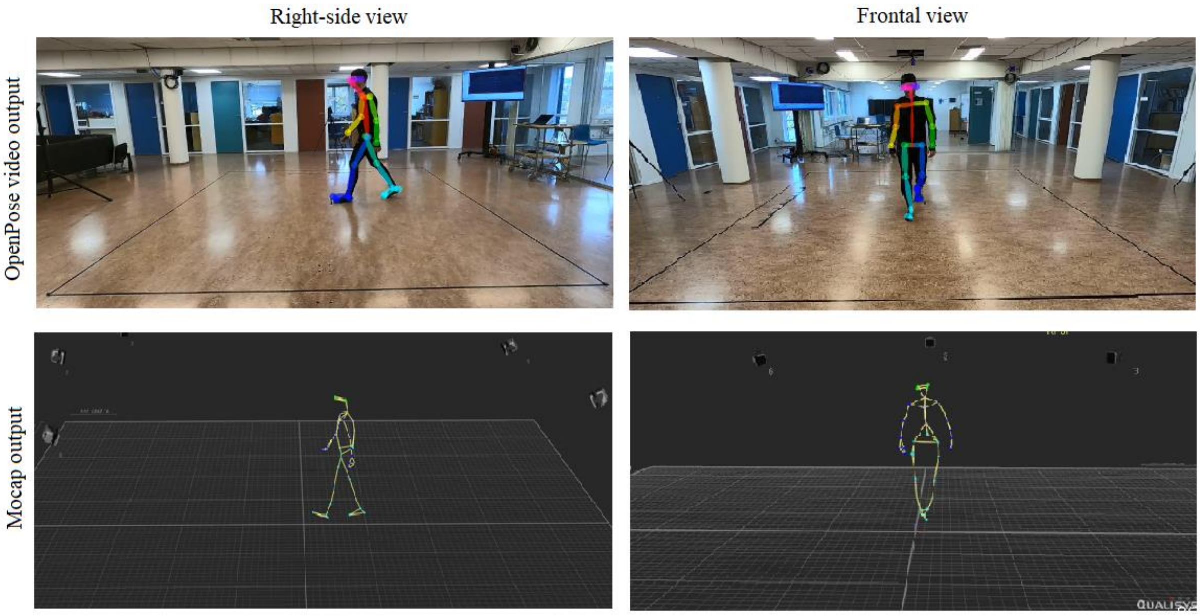

Figure 2) View walks from pose tracking video and Motion capture record of the front and right-side camera

Correlation Analysis

To find the appropriate type of correlation in this case, the normality assumption of the gait parameters was evaluated. Using the Shapiro-Wilks test for normality, significant p-values (less than 0.05) were obtained for three of the gait parameters (swing time, double support time, and step width) which did not satisfy the normality assumption. It indicated the choice for the type of correlation test, which was Spearman correlation.

Spearman's correlation results for the gait variables from the motion capture and the OpenPose estimation are presented in Figure 8 and Table 3. It is observed that five out of six gait parameters show strong correlations namely the step time, stance time and double support time measures with very high correlation values ($Rs > 0.9$, p-value < 0.001), step length and swing time variables with high correlations ($Rs > 0.7$, p-value < 0.001). However, the step width is the only parameter that designates low correlation and insignificant p-value ($Rs = 0.29$, p-value $= 0.23$) possibly due to the effect of frontal plane video perspective on the scaling of pixels to meters, since the values obtained from the pose estimation are dimensionless and cannot be directly compared with motion capture values; This conversion of pixels to meters introduced error.

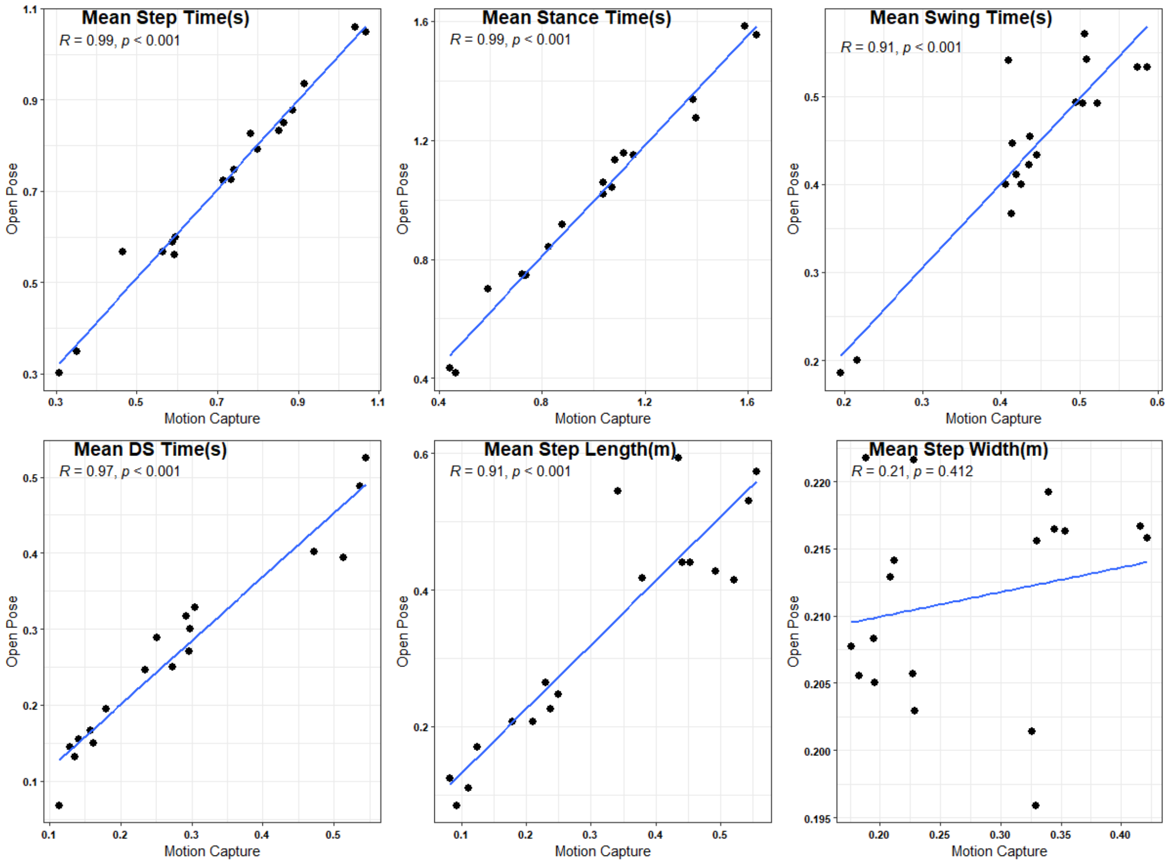

Figure 3) Scatter plots for all gait parameters including mean of steps captured from Motion Capture and OpenPose; The blue line is the fitted line. The correlation coefficient and p-value are shown in the figures.

Table 12) Results of correlation analysis between gait variables calculated from the motion capture and from the OpenPose tracking; *, significant p < 0,05

Gait parameters	**Spearman correlation**	
	R_s	p-value
Step Time(s)	0,98	< 0,001*
Stance Time(s)	0,98	< 0,001*
Swing Time(s)	0,74	< 0,001*
Double support time(s)	0,97	< 0,001*
Step Length(m)	0,85	< 0,001*
Step Width(m)	0,29	0,23

Logistic Regression

To determine the effect of each predictor on the response variable, a forward logistic regression approach is used such that the predictors are added to the model in turn. Since the number of observations in this study are limited, the better way of studying the relationships is the conservative approach. Of course, a complete model with all the independent variables entering the model at the same time is fitted after the forward approach to make sure about the effect of each independent variable's presence on the response variable in the model.

First, the one-predictor model using step time was fitted. The result (Table *4*) shows that the p-values are significantly greater than 0.05, which states there is no statistically significant relationship between the system type and step time. Therefore, we strongly (p-value = 0,95) accept the null hypothesis for this variable, it approves that step time measures in both systems are statistically the same.

Then, the second predictor, stance time, is added to the model. From the result (Table 5) it is observed that there is no association between any of the two predictors (stance time and step time) and the system type. Having the p-value > 0.7 for both of independent variables, lead to accepting the null hypothesis strongly. As looking at the results step time is still insignificant in the model even after entering stance time.

Next, in the third turn, the three-predictor model is fitted, by adding swing time parameter. As it can be seen in Table 6, by adding the swing time to the model, the p-values for all three predictors still are highly insignificant.

Then, double support time as the next independent variable is inserted to the model. A decrease in two out of three p-values of the predictors (step time and swing time) in the model is shown from the result (Table 7) after entering the double support time to the model compared to the previous step. However, the insignificancy of all four predictors relative to the system type is obtained, which again confirms no meaningful difference between Mocap and OpenPose.

Next, step length is added to the model as predictor. Having five independent variables in the fitted model, shows high p-value for two of them (stance time and step length) and moderate level for the other three (Table 8). The evidence approves that the null hypothesis is accepted again.

In the last run of the fitting model, the predictor step width is inserted. Opposing the previous steps, a significant p-value (0.006) is showed up referring to adding the predictor step width in the model (Table 9). It represents that there is an association between the step width and the type of system such that step width is different for each level of system type meaning that it has a significant relationship with the system type. The same result for this variable was obtained in the correlation analysis part also. Except step width, all other five independent variables are still confirming that there is no relationship between them and the system type.

The forward approach and the complete model are in line considering hypothesis testing results.

From the regression analysis results step time, stance time, swing time, DS time and step length proved to be insignificant in the relationship with the system type. For further clarification the above-mentioned independent variables have no statistically significant effect on system type. Also, the only significant independent variable is step width which the p-value resulting from the test is relatively less than 0.05.

Table 3) Results of Logistic regression model in different runs per entering the predictors in turn to the model; *, significant $p < 0{,}05$, The results are rounded up to 2-digits.

	one-predictor			**two-predictor**			**three-predictor**			**four-predictor**			**five-predictor**			**six-predictor**		
Predictors	Estimate	Statistic	**p-value**	Estimate	Statistic	**p-value**	Estimate	Statistic	**p-value**	Estimate	Statistic	**p-value**	Estimate	Statistic	**p-value**	Estimate	Statistic	**p-value**
(Intercept)	0.92	-0.07	0.947	0.79	-0.19	0.852	1.04	0.03	0.979	0.76	-0.18	0.861	0.75	-0.19	0.851	235200.03	16469	0.014*
Step time	0.12	0.07	0.945	8.65	0.35	0.725	167.21	0.51	0.608	1027.4	0.67	0.5	21916.24	0.78	0.434	811555556	45658	0.212
Stance time	-	-	-	0.27	-0.35	0.729	0.09	-0.5	0.615	25.12	0.47	0.641	31107	0.16	0.87	0.09	-0.23	0.814
Swing time	-	-	-	-	-	-	0.05	-0.38	0.704	0	-0.96	0.336	0	-0.99	0.322	0	-1.87	0.062
DS time	-	-	-	-	-	-	-	-	-	0	-1.16	0.245	0	-0.88	0.38	4.95	0.09	0.926
Step Length	-	-	-	-	-	-	-	-	-	-	-	-	4.96	0.41	0.679	5.59	0.37	0.709
Step width	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0	-2.76	0.006*
Observations	*36*																	

PLS-DA Modelling

To assess the ability of the pose tracking algorithm (OpenPose) in differentiating the measured types of gait, Partial Least-Squares Discriminant Analysis (PLS-DA) is performed. PLS-DA is a machine learning tool that is being used increasingly as feature selector and classifier. It is a combination of principal component and regression analyses to extract key features by modeling covariance structures. As a linear, multivariate model, PLS-DA, use the partial least square (PLS) algorithm to classifies the labelled data by finding the components that best separate the sample groups (Ruiz-Perez, et al., 2020) (Zhou, et al., 2020). It has well performance for the data with multiple independent variables and lower number of observations (Eriksson, et al., 2006), which is present in the case of this study.

In the PLS analysis the main goal is to define a maximum covariance model and explain the relationship between the gait variables (predictors) and system type, OP and MC (responses). To this end, successive orthogonal factors are selected that maximize the covariance between each predictor and the corresponding response to find a model that best assign the system type with a selected number of gait variables.

The input data in performing the PLS-DA analysis, consists of the gait variables (predictors) which formed the X-matrix, and the system type (response) as the Y-matrix; For the discriminant analysis, the observations separated to five groups according to the five different type of walking pose namely normal, slow, short, wide, and limp. Gait variables include step time, stance time, swing time, double support time, step length and step width. The PLS-DA model is constructed using R software.

In the model two principal components (comp1 and comp2) are considered. It classifies the two samples of measuring systems (OP and MC) into known groups of gait type (normal, slow, short, wide, and limp) by finding patterns and relations between all the extracted gait parameters, test conditions, and measuring systems. The result of the model is visualized as shown in the Figure 9. This star plot considering the observations from both measuring systems together and shows the clustering of each sample according to the gait type by different colors, the arrows from each group shows centroid towards each individual sample, the confidence ellipses are plotted for each sample and the confidence level set to 95%. Some discrimination can be seen between the slow gait and wide gait samples vs. the others on the first component (x-axis), and normal, limp, and short gait vs. the others on the second component (y-axis).

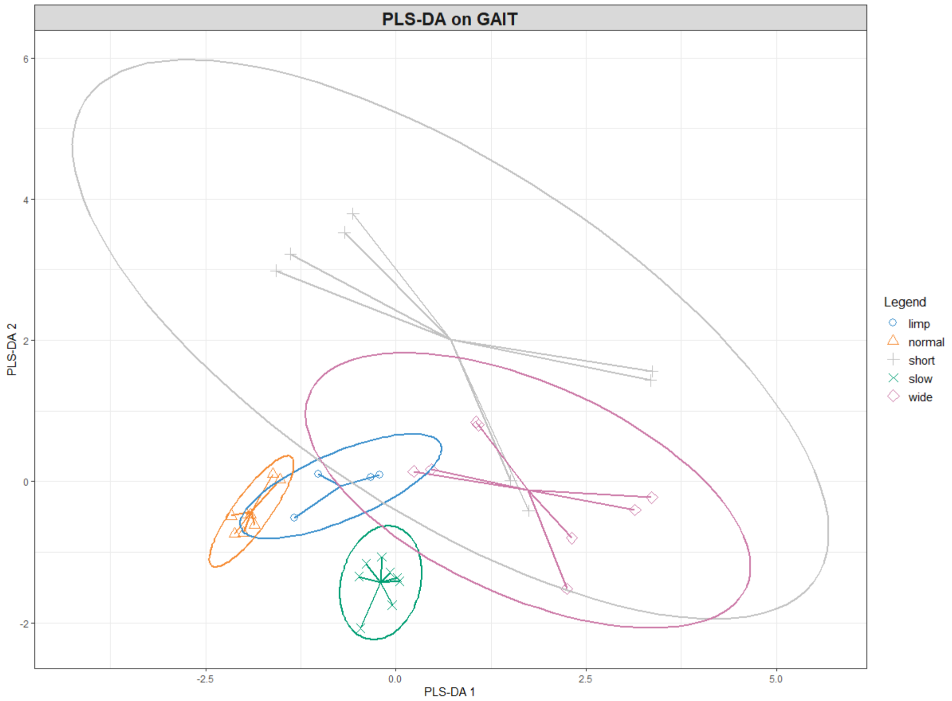

Figure 4) Star plot of PLS-DA clusters, different gait types are shown in different colors, x-axis shows the first component, and the y-axis represents the second component

To show how the observations measured by each system is located in the gait-type-based clusters another visualization of the PLS-DA with the detailed of system type (OP and MC) is presented Figure 5.

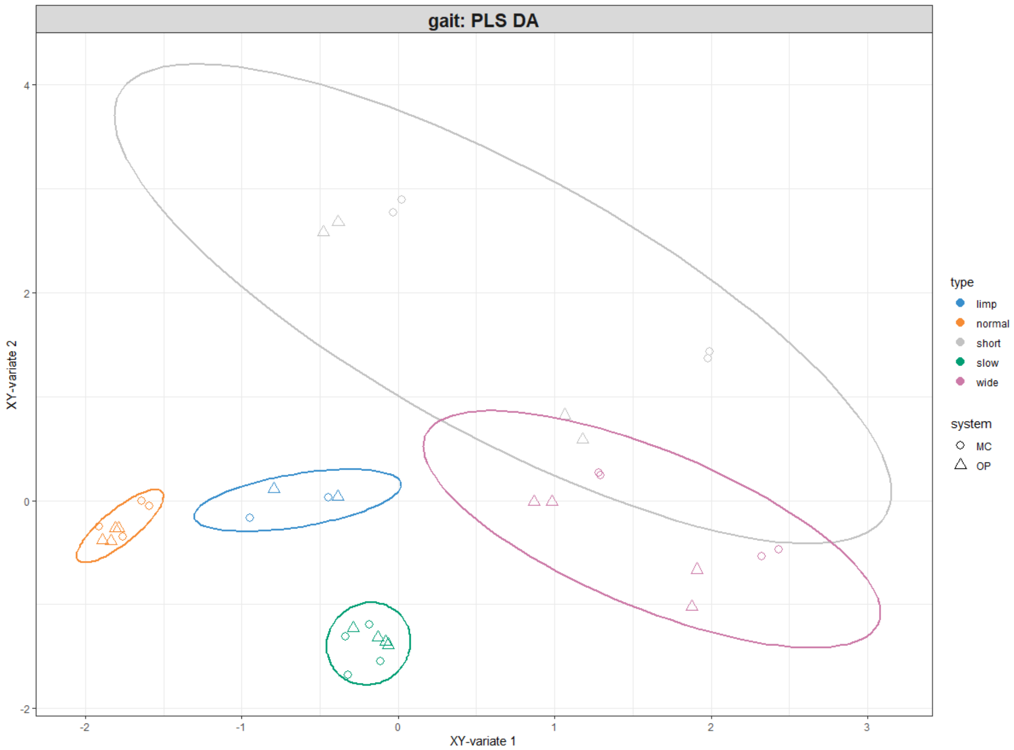

Figure 5) PLSDA plot showing clusters of different gait types in different colors, x-axis shows the first component, and the y-axis represents the second component, MC refers to motion capture, and OP means OpenPose

The distinction shown in the above graph represents that the PLSDA model differentiates between different types of gait including normal, slow, short, wide, and limp in both Motion capture and OpenPose in similar clusters and shows no major differences between MC and OP measure-methods.

5.2 Balance results

To compare two groups of CoM data provided from the four balance trials recorded by Mocap and OpenPose, the means of two samples are tested against each other. For that first the normality of the data is investigated. Since the size of the balance dataset is large, the Jarque–Bera test is considered to verify if the data are normally distributed or not. According to the test result, the obtained p-value is close to zero, therefore data showed non-normality. Due to the non-normality of data, the unpaired two-samples Wilcoxon test which is a non-parametric alternative to the unpaired two-samples t-test is performed. For each test the p-value is calculated using R software. The attained p-value in the first trial of balance test, equals to 0.97 which is strongly insignificant and toward accepting the null hypothesis and shows that mean level of both samples is the same. In the two other balance trials and also in abnormal balance trial, p-value shows insignificant values, confirming that both Mocap and OpenPose are in well agreement with each other.

6. DISCUSSION

We examined the performance of pose estimation (OpenPose) in detecting different types of postures both for walking (normal, slow, wide, limp, and short walking types) and balance experiments (normal and abnormal balance) by comparing the quantitative 2D spatiotemporal gait measurements against a golden standard. The comparisons were performed for videos captured by front and right-side cameras.

Results from our research indicate that five out of six gait parameters namely the step time, stance time, and double support time measures calculated from the OpenPose correlate significantly to that of the motion capture system. However, the step width is the only parameter that designates a low correlation between them. Similarly, the results from logistic regression modeling showed insignificant relationship between these five gait parameters and the two pose capturing tools (Mocap and Openpose), while step width represented a relatively significant effect on them. It might be due to the effect of frontal plane video perspective on the scaling of pixels to meters, since the values obtained from the pose estimation are dimensionless and cannot be directly compared with motion capture values; This conversion of pixels to meters introduced error. The PLS-DA model (Partial Least Square Discriminant Analysis) demonstrated that gait variables extracted from OpenPose and Motion capture can be discriminated in clusters based on gait type with no major differences between OpenPose and Mocap. Also, the results from a two-group comparison test (Wilcoxon) on balance parameter (CoM values) between Mocap and OpenPose showed that the mean level of both samples is the same in four different balance trials, including three balance trials and one imbalanced experiment.

Overall, the results suggest that pose estimation showed promising performance in discriminating among normal and abnormal poses as compared to the golden standard (Mocap) in both walking and gait experiments.

The findings of this study are in line with the recent studies using OpenPose in terms of its robustness for two-dimensional analysis of human pose (Cao, et al., 2019) (Chen, 2019) (Kim, et al., 2021) (Li, et al., 2021) (Mehdizadeh, et al., 2021) (Stenum, et al., 2021), which could be considered as the next achievement to the chain of forward research in human movement context. While gait and balance are among key human movement to be assessed in ergonomics research using pose estimation, other common occupational postures in different workplaces can be considered in future studies.

Using wearable sensor-based tools vs video pose estimation for human postural analysis is a controversial issue. This is a discussion among researchers, ergonomists, workers, employers, and clinicians, with advantages and disadvantages on both sides (sensors vs video pose estimation). On one hand, video pose estimation might allow activity assessment without placing sensors on people and might be cheaper if it can be done with conventional video cameras. On the other hand, there is the issue of privacy, data security, and monitoring, where video data is significantly more sensitive than data from movement sensors. To sum up, it depends a lot on the final application, and the availability of resources for safe and ethical data management if video is to be collected on regular basis at the workplace.

Furthermore, the limited dataset of our work due to the performed preliminary experimental research could be considered for future studies, which suggests the need for a more systematic data collection protocol that could also aid in improving data quality and facilitating the acquisition of larger datasets.

In experimental aspect, estimation of step lengths and widths with pose estimation is influenced by the position of the participant along the field of view of the camera. To generate estimates of spatial gait parameters (e.g., gait speed, step length) it is necessary to scale the video. Here, we accomplished this by scaling the video to known measurements on the ground. The process for scaling frontal plane video requires additional linear interpolation to account for changes in the distance to the field of progression during gait (participant walking away or towards the camera is seen in pose estimation as a change in height in screen coordinates).

Although stationary camera recordings for sagittal plane with consistent camera height gave the best results. Frontal plane video results could be improved if the camera follows the participant at a fixed distance and with minimal height changes. The developed framework relies on several post-processing steps, some of which were completed manually. This includes detection of multiple persons, left-right limb switching and gaps in the data.

We anticipate that clinical video-based analyses will be performed on videos taken by smartphone, tablets, or other household electronic devices. Many of these devices have standard frame rates of 30 Hz during video recording are comparable to the ones used in this study.

We did not directly compare the results of our pose estimation analyses to results of any other markerless approaches (e.g., Kinect), nor did we run a comparison with other available pose estimation algorithms (DeepPose, DeepLabCut, OpenPifPaf). Pose estimation methods do not track movements of the human body perfectly from frame-to-frame. The body key points are unlikely to be equivalent to the marker landmarks as they rely on visually labeled generalized points (e.g., “ankle”, “knee”) whereas motion capture marker placement relies on manual palpation of bony landmarks. Pose estimation methods are also capable of three-dimensional human movement analysis through multiple simultaneous camera recordings.

Here, we assumed that most videos taken in the home or clinic will be recorded by a single device, thus, we limited this study to two dimensional analyses of human walking and balance. We used a pre-trained network provided by Open-Pose to avoid spending time and resources training our own network. However, it may be possible to obtain more accurate video-based analyses by training gait- and balance-specific networks from different views (e.g., sagittal, frontal) and for different movement conditions.

7. CONCLUSION

This study provides preliminary evidence that pose estimation (using OpenPose) could work as a tool for quantitative 2D spatiotemporal analyses of gait and balance as the key human movements to be referred in ergonomics postural assessment. Pose estimation (OpenPose) were compared to a golden standard (Mocap) through a set of physical pose-based tests. The experiments were two-fold: Gait trials that were tested under five different status including normal, slow, short, wide, and limp, and balance posture which were examined on normal and abnormal positions. Overall, the results suggest that pose estimation showed promising performance in discriminating among normal and abnormal poses as compared to the golden standard (Mocap) in both experiments. Therefore, this reveals the potential for three-dimensional pose estimation using multicamera setups in future researches.

However, the same results from the two performed statistical tests namely correlation analysis and logistic regression were obtained in the gait parameters measurements; It represented that pose estimation showed agreement with the golden standard (Mocap) in measuring step time, stance time, double support time and step length, and only in estimating step width it demonstrated relatively poor performance. It might be due to the effect of frontal plane video perspective on the scaling of pixels to meters. Hence, future studies should be engaged in developing and validating a more precise pose estimation from frontal views.

Furthermore, the limited dataset of our work due to the performed preliminary experimental research could be considered for future studies, which suggests the need for a more systematic data collection protocol that could also aid in improving data quality and facilitating the acquisition of larger datasets.

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