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Faculteit Revalidatiewetenschappen

master in de revalidatiewetenschappen en de kinesitherapie

Masterthesis

Tracking joint centres with the use of DeepLabCut in comparison to manual annotation: a study on concurrent validity

Brice Seymens
Ties Thys

Scriptie ingediend tot het behalen van de graad van master in de revalidatiewetenschappen en de kinesitherapie, afstudeerrichting revalidatiewetenschappen en kinesitherapie bij musculoskeletale aandoeningen

PROMOTOR :
Prof. dr. Pieter MEYNS

COPROMOTOR :
dr. Maud VAN DEN BOGAART

2022
2023

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www.uhasselt.be
Universiteit Hasselt
Campus Hasselt:
Martelarenlaan 42 | 3500 Hasselt
Campus Diepenbeek:
Agoralaan Gebouw D | 3590 Diepenbeek

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"Is DeepLabCut valid for measuring joint centres in the frontal plane in healthy adults during gait and jogging when compared to manual annotation with the Kinovea software?

Highlights:

- Phases of gait with greater amplitude of movement cause greater differences between systems.
- DeepLabCut is not valid for tracking joint centres in the frontal plane during walking and jogging in comparison to manual annotation .
- Further research is recommended to improve the accuracy of deep learning software to recognise joint centres in videos and to improve its validity for tracking joint centres in the frontal plane.

Authors
Seymens Brice & Thys Ties

Promotor
Prof. Dr. Pieter Meyns

Supervisor
Dr. Maud van den Bogaart

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We would like to thank Hasselt University for the knowledge and experiences they provided us throughout our study in Rehabilitation Sciences and Physical Therapy.

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Kerkstraat 18, 2480 Dessel, 31/05/2023 T.T

Rozenberg 37/1, 2400 Mol, 31/05/2023 B.S.

Research context

This master's thesis is commissioned by the Hasselt University and is part of the Biomechanical research domain. This master's thesis research was conducted under the supervision of promotor Prof. Dr. Pieter Meyns and supervisor Dr. Maud van den Bogaart. It forms part of a bigger research on the Luxonis OAK-1 cameras, DeepLabCut, Kinovea and GaitRite systems for measuring kinematic - and spatiotemporal data during the walking and running of healthy adults.
Technology is a fast evolving field in today's world. It is getting more common to use in different fields. One of these is the field of biomechanics, which is an important part of sports - as well as rehabilitation sciences. Movement analysis is becoming easier and more accurate because of the advancements in recent technology. To conduct movement analysis motion capture can be used. To optimise the analysis of movement, the motion capture and the data output should be as accurate as possible. One type of data gathered from motion capture is data on the kinematics. Three-dimensional (3D) marker based motion capture is the current gold standard for capturing kinematic data. However it has a few drawbacks such as the markers applied to the subjects body possibly restricting movement or being placed inaccurately. There is also a high financial cost to marker based motion capture and it requires trained experts to set up the system and use it (Simon, S.R., 2004; Harris, G.F. & Smith, P.A., 1996; Grigg et al., 2018; Bahadori et al., 2019; Camomilla et al., 2017, Roggio et al., 2021). Markerless motion capture makes the process of capturing kinematic data easier since it removes the reliance on physical markers. It also aims to expand the environment in which motion capture can be used (Kanko et al., 2021; Kanko et al., 2021; Cronin et al., 2019). Because motion capture and movement analysis have their place in rehabilitation (Wong et al., 2007) , it could be helpful to have free, accurate and valid motion capture solutions to make it more accessible in a functional environment.

The protocol for this study was written by two other students in their first master's year at the University of Hasselt at the faculty of Rehabilitation Sciences and Physical Therapy. The experimental set up in this protocol was a conjoined effort of the students who have written the protocol and the two students who have conducted and written this master's thesis study. Engineer Geraerts M. supported the technical side of the experimental setup.

The recruitment of participants was done via the personal network of the four previously mentioned students. The same students were involved in the collection of the data for this master's thesis. The data processing of the manual annotation through the Kinovea software was done by the writers of this master's thesis, supervisor Van Den Bogaart M. was responsible for the data processing through DeepLabCut. Supervisor Van Den Bogaart M. also executed the Statistical Parametric Mapping in Matlab and provided the required output for this master's thesis. Statistical analysis in SPSS was the responsibility of the students and was checked by the supervisor. The students wrote this master's thesis on their own, sending draft versions to their supervisors for feedback on previously agreed moments. The feedback received was applied as soon as possible.

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Table of contents

1. Abstract

Background DeepLabCut (DLC) is an open-source machine-learning-based video analysis software that can be used to measure joint centre locations on simple video recordings. . DLC is shown to be valid for measuring joint angles in the sagittal plane during a vertical jump in healthy humans but there is no evidence yet for the validity of DLC for tracking frontal plane joint centres in humans during gait.

Objectives To determine the validity of DLC in comparison to manual annotation in Kinovea for tracking joint centres during walking and jogging in the frontal plane.

Participants 20 healthy adults (15 male / 5 female) between the ages of 18 and 65 years old were included.

Methods All participants completed five walking and jogging trials. A video camera at the end of the 5.16 meter long walkway recorded these. Kinovea and DLC were used to estimate the X- and Y-coordinates of the joint centres from shoulders, elbows, wrists, hips, knees and ankles during the first stride of each task. To evaluate the agreement between both systems, linear mixed model analysis was performed in SPSS using type III fixed effects tests and two way repeated measures ANOVA was used for Statistical Parameter Mapping (SPM). Main effects of the systems, tasks and interaction effects between these two were analysed.

Results Significant differences were found between the two systems. The left hip joint had the greatest between-system difference ($p < 0.001$). Y-axis coordinates showed greater differences between the systems when Y-axis displacement during movement was larger ($p < 0.001$).

Conclusions Frontal plane joint centres assessed with DeepLabCut are not valid with respect to manual annotation in Kinovea software. Training the model more could possibly increase the performance of the system.

Keywords Deep learning, joint centres, markerless motion capture, gait

2. Introduction

The aim of human movement analysis is to gather quantitative information about the mechanics of the musculo-skeletal system during the performance of a motor task (Cappozzo et al., 2005)[3]. Possible applications can be found in a sport- or rehabilitation setting. In the first it can be used to measure sport performance (Chiu et al., 2014)[4], for technique evaluation (Huchez et al., 2015)[11] and for injury prevention (Sinclair, J. & Bottoms, L., 2013)[23]. Some examples of how movement analysis can be used in a rehabilitation setting include gait analysis, posture and trunk movement - and upper limb movement analysis. Observations of different movement strategies and biomechanical constraints could be done and afterwards implemented in rehabilitation if needed(Wong et al., 2007)[26]. Kinematic data for these analyses can be estimated via motion capture (Sutherland, D.H., 2002)[24]. Kinematics cover the geometric description of movements of the individual body segments and their positions relative to each other (Oppelt et al., 2020)[18]. Joint centres, which act as an axis for connecting segments, form an important part of kinematics since angles can be estimated using them.

The current gold standard for motion capture is Three dimensional (3D) marker-based motion capture (Krigslund et al., 2012; Munro et al., 2012)[14, 15]. This method captures motion using a Optoelectronic stereophotogrammetric multi-camera capturing system by tracking physical markers placed on the body (Roggio et al., 2021)[20]. The downsides of marker-based motion capture are the time consumption, movement restriction by the placed markers, incorrect placement of markers by human error, soft tissue artefacts, space required for the setup, high financial cost and the need for trained professionals.The downsides of marker-based motion capture are the time consumption, movement restriction by the placed markers, incorrect placement of markers by human error, soft tissue artefacts, space required for the setup, high financial cost and the need for trained professionals. (Bahadori et al., 2019; Camomilla et al., 2017; Grigg et al., 2018; Harris, G.F. & Smith, P.A., 1996)[1-2, 9-10].

A more affordable method to analyse movement is manual annotation by applying digital markers on a video. One of the primary advantages of manual annotation of the markers is that there is no need for attaching physical markers to the subject's skin. This makes this method a valuable tool in sports biomechanics as it makes it possible to analyse movements in normal training- and competition situations. This method makes it more accessible to perform gait analysis in therapeutic settings (Churchill et al., 2002)[5]. But manual annotation also has certain drawbacks. Manually annotating joint centres is a time-consuming and laborious process, and is liable to subjective errors.An example of a software for manual annotation is Kinovea. Schurr et al., 2017 [22] found Kinovea to be comparable to 3D motion capture systems for kinematic analyses of all joints in the sagittal plane, but only for the knee in the frontal plane. The Kinovea software is found to be valid and reliable for measuring angles and distances by using coordinates (Puig-Diví et al., 2019)[19].

A third method for motion capture is markerless motion capture. These systems estimate joint centres in video recordings by using a deep learning algorithm which is trained to identify patterns between images and their labels. In this case the labels show the location of the corresponding joint centres in the image (Kanko et al., 2021; Cunningham et al., 2008)[12, 7]. Markerless motion capture makes collecting data easier since it removes the reliance on physical markers. It may improve the reliability of data by removing the human error in marker placement, but can have a small decrease in pose estimation performance (Needham et al. 2021)[17]. It could expand the use of movement analysis to instances where marker-based motion capture cannot be used, since the last mentioned can only be used in a laboratory-based setting (Cronin et al., 2019; Kanko et al., 2021)[6, 13]. A lot of the algorithms such as OpenPose and DeepPose used for markerless motion capture require large labelled data-sets to learn. DeepLabCut (DLC) is a markerless motion capture algorithm that can be trained on smaller data-sets. Pretrained models can be used to speed up the model training process as only the final layer of the algorithm network remains to be trained. DLC has been studied on animals ranging from insects such as flies to larger animals such as horses for pose estimation outside of a laboratory environment (Nath et al., 2019)[16]. Next to that it has been validated for measuring sagittal plane lower body joint angles of healthy adults during a vertical jump task, in comparison to a marker based system (Drazan et al., 2021)[8]. But there is no evidence yet on the validity of DLC to measure kinematic data in the frontal plane during everyday tasks such as walking and jogging.

The aim of this study is to compare the concurrent validity of a markerless motion tracking system (DeepLabCut) with manual annotation software (Kinovea) to track full body joint centres during gait and jogging of healthy adults in the frontal plane.

3. Methods

3.1 Research question

Is DeepLabCut valid for measuring joint centres in the frontal plane in healthy adults during gait and jogging when compared to manual annotation with the Kinovea software?

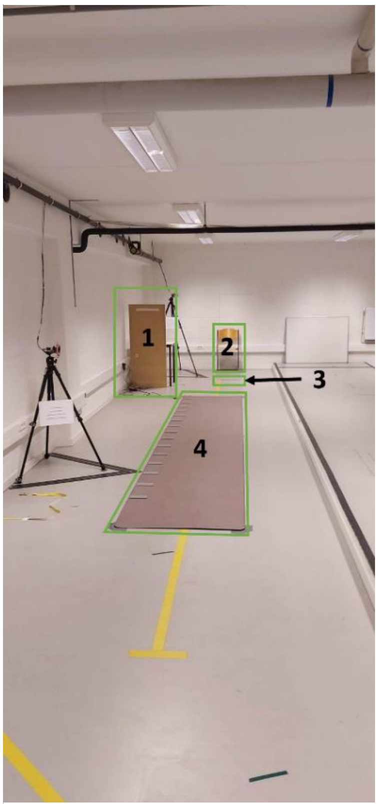
3.2 Participants

Participants were recruited through the personal network of the researchers. They needed to be healthy male or females between the ages of 18 and 64 years old and were all able to walk independently without assistive devices. They were excluded from the study when they had any orthopaedic or neurological disorders, underwent orthopaedic or neurological surgery in the last 24 months or if they had symptoms of COVID. All participants included in this study signed an informed consent and filled in a questionnaire about the inclusion and exclusion criteria of this study. This study was ethically approved by the ethics committee of Hasselt University (Martelarenlaan 42 - 3500 Hasselt, 07/04/2022, MOVING; CME2022/006).

3.3 Materials and setup

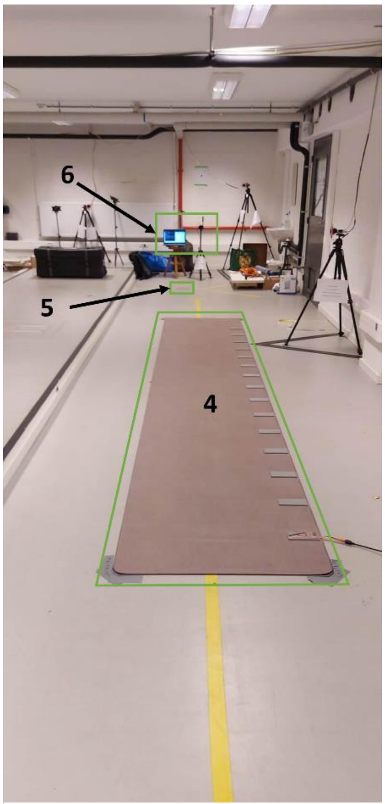
A 5.16m by 0.89m GAITRite walkway was placed in an open space in a research lab of the faculty of rehabilitation sciences at Hasselt University, with a start line 1.70m before the mat and a stop line 1.40m behind the mat. Two Luxonis OAK-1 cameras were used. These cameras are capable of capturing high resolution images (4056 x 3040), running custom Artificial Intelligence models and performing advanced computer vision tasks. One camera was placed at the middle and 5m to the left of the GAITRite walkway at a height of 0.805m for capturing sagittal plane recordings. The other camera was placed 3m behind the end of the GAITRite walkway at a height of 0.805m facing the frontal plane of the participants. Both cameras were programmed to capture 24 frames per second (fps). Only the camera facing the frontal plane was used for this study. A pc was placed next to each OAK-1 camera to run the camera software and store the video files. Above the camera in the sagittal plane, a 10000 lumens 200W Hoftronic floodlight was placed to reduce the motion blur in the recordings. One pc was used to collect data of the GAITRite walkway. This pc was placed on a desk at the start of the GAITRite walkway behind a screen so the examiner controlling the GAITRite software remained out of sight of the OAK-1 cameras during the test procedure. This prevented interference of the examiner with the software. The setup is shown in Fig. 1-2.

Figure 1
Experimental setup



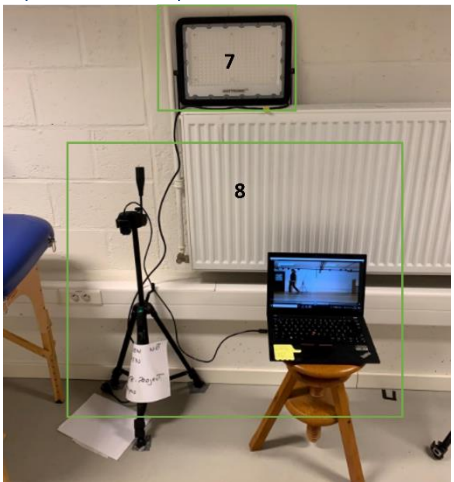
1: Screen to cover researcher; 2: Chair for the subject; 3: Startline; 4: GaitRite walkway

Figure 2
Experimental setup



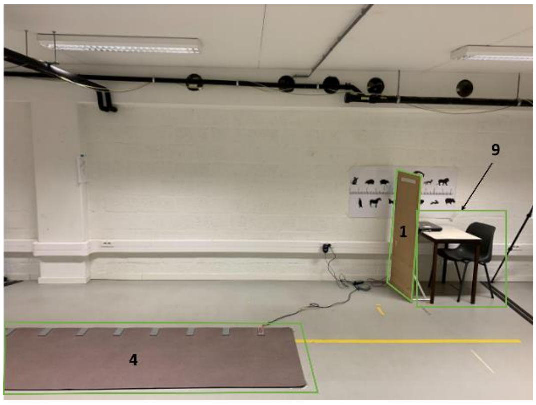
4: GaitRite walkway; 5: Stopline; 6: Frontal OAK-1 camera and pc

Figure 3
Experimental setup



7: Hoftronic Floodlight; 8: Sagittal OAK-1 camera and pc

Figure 4
Experimental setup



1: Screen to cover researcher; 4: GaitRite walkway; 9: Desk with pc for GaitRite system

3.4 Data collection procedures

3.4.1 *Preparation participants*

Participants signed the written informed consent and filled in a questionnaire to make sure criteria for eligibility were met. Afterwards they changed into the required clothes (black shorts, black shirt and sneakers or running shoes), were weighed and the height and leg length of both legs of the subject were measured before the start of data collection. Finally the participant was placed at a chair in front of the start of the GAITRite walkway to start the data-collection.

3.4.2 Preparation materials

The examiner started the recording on the OAK-1 camera in the frontal plane, followed by the start of the recording of the OAK-1 camera in the sagittal plane. The recordings on these cameras weren't stopped until the data collection of the subject was finished.

3.4.3 Data-collection

The participants were asked to complete five trials of walking and jogging at a comfortable pace. Randomisation of the trial order was done by asking the participant to draw a card with a number on it, which corresponds with a task. Two practice trials were done for the first task at the beginning of the data collection to make sure that the participant understood the assignment. The participant started walking or jogging before the GAITRite walkway and continued walking or jogging until the marked end point was reached, to make sure there was minimal acceleration and deceleration on the Gaitrite walkway.

3.5 Data processing

After recording the video, it was cut in separate videos of each trial. Each video started at the first heel contact of the left foot on the GaitRite walkway and ended at the last toe off of the left foot on the walkway. The first stride of each task was used to compare the validity of DeepLabCut to Kinovea. The joint centres of the ankles, knees, hips, wrists, elbow and shoulders were annotated in the Kinovea software with the origin being placed in the left upper corner of the video screen. Kinovea software has an auto tracking feature which was enabled during manual annotation. The joint centre location was checked on every frame and corrected when necessary. The X- and Y-coordinates of the joint centres were exported to a Microsoft Excel file, in which the exact times of heel strikes of the left foot were marked by synchronising the video time with the heelstrike times reported by the GaitRite system. DeepLabCut (DLC) was used for markerless annotation of the joint centres on the exact same video files. The coordinates of the joint centres found with DeepLabCut were also exported to a Microsoft Excel file to compare the two methods. The DeepLabCut algorithm was trained using the pretrained MPII human model. For further training of this biomechanical model, an extra 64 frames were labelled with the same joint centres as in Kinovea. These frames came from eight video recordings of eight different subjects included in this research. This model was then trained to 260000 iterations. A batch size of eight was used in combination with a Resnet_101 convolutional neural network and a training fraction of 95%. Only data points with a likelihood greater than 0.8 ($p > 0.8$) were used in the analysis. Finally the data of the strides was normalised, to make sure that every stride had the exact same duration (1-101). Making it possible to compare time-normalised data points at different phases of the gait cycle. This was done for analysis in SPM, but not for analysis in SPSS. Not all joints were included for the statistical analysis due to the fact that further processing was needed to include them in this master thesis. Data of X-values of both elbow and knee joints and the Y-coordinates of right elbow, left hip and right knee was included.

3.6 Statistical analysis

Statistical analysis was executed in SPSS (IBM SPSS Statistics v28.0.1.1 (15), www.IBM.com) using a linear mixed model on the not time-normalised dataset to evaluate the agreement of both methods of joint centre tracking (concurrent validity), taking the interaction effect of system and task into consideration. A two-way repeated measures ANOVA Statistical Parametric Mapping (SPM) (SPM1d vM.0.4.5, www.spm1D.org) was performed for the comparison of time-normalised data points.

3.6.1 SPSS

Statistical analysis in SPSS was performed using linear mixed models. The assumption of normality was not checked, since fixed effects estimates of mixed models are not severely affected by violations of assumptions (Schielzeth et al.,2020)[21]. A priori, an alpha level of 0.05 was set. Type III tests of fixed effects (F-statistics) were used to evaluate if there was a significant difference between the two systems (DLC and Kinovea), via the main effect system, and if there was an influence of the task on the agreement between systems, via the interaction effect of the system and task (walking and jogging). If there was no significant interaction found, the mixed effects analysis was performed again with the non-significant effects removed from the model. If a significant interaction was present, a post hoc analysis was done for the separate tasks to determine what task held the significant difference between the two methods. In this case the level of significance was corrected using a Bonferroni correction ($p \leq 0.05/2 = p \leq 0.025$).

3.6.2 SPM

Biomechanical waveforms of all time-normalised data points were plotted for each joint included in this research. Normality was checked for the SPM analysis. If the time-normalised data of the joint was normally distributed a parametric test was used, if not a non-parametric test was performed. Differences between the waveforms were analysed to compare the tracking of joint centres of DLC to Kinovea by using SPM analysis in MATLAB (version R2022b; 9.13). Results were shown for main effect system (DLC and Kinovea), 16main effect task (walking and jogging) and the interaction effect between those two in graphs that show where the differences between the two systems are significant ($p \leq 0.05$). If there were significant differences found in the interaction graph, post hoc analyses were done for the separate tasks and the level of significance was corrected using a Bonferroni correction ($p \leq 0.05/2 = p \leq 0.025$).

4 Results

4.1 Participants

20 participants were found to be eligible for and were included in this study. Five were female and fifteen were of the male gender. The ages ranged from 19 to 59 years old (mean age 27.1±11.72) and the mean BMI was found to be 24.051. All participants completed all the trials. Participant characteristics can be found in Table 1.

Table 1
Participant Characteristics

Subject #	Age	BMI	Sex	Subject #	Age	Sex	BMI
0001	26	24.38	M	0011	21	M	19.93
0002	23	23.99	M	0012	26	F	27.36
0003	22	24.49	M	0013	21	M	19.15
0004	51	29.83	M	0014	19	M	22.10
0005	51	29.41	F	0015	20	F	21.80
0006	23	19.84	M	0016	20	M	22.99
0007	59	26.90	F	0017	21	F	22.91
0008	22	23.33	M	0018	22	M	24.62
0009	22	21.56	M	0019	22	M	22.80
0010	25	22.16	M	0020	26	M	31.46

4.2 Statistical analysis

4.2.1 SPSS

A summary of the SPSS results with corresponding F- and p-values can be found in table 2-3.

4.2.1.1 System comparison

When comparing DLC with respect to Kinovea, significant differences were observed for all included joint centre coordinates, except for the X-coordinates of the right elbow (p: 0.120) and right knee (p: 0.117).

4.2.1.2 Interactions

A significant interaction was found for the trial- and system effects of the right knee Y-values. After the post hoc analysis a significant between-system difference was found during the jogging task (p: 0.005), but not for the walking task (p: 0.368). Interactions were not significant for the other included joints centres.

Table 2
SPSS Type III test outcomes for each joint. (α = 0.05)

Joint	*Coordinate*	*Side*	*Statistical outcome*
Elbow	X	Left	System effect: F: 8.932 p: 0.003 Interaction task X system: Not significant
		Right	System effect: F: 2.413 p: 0.120 Interaction task X system: Not significant
	Y	Left	Not included in this research
		Right	System effect: F: 4.882 p: 0.027 Interaction task X system: Not significant

Hip	Y	Left	System effect: F: 966.630 p: <0.001 Interaction task X system: Not significant
		Right	Not included in this research
Knee	X	Left	System effect: F: 25.249 p: <0.001 Interaction task X system: Not significant
		Right	System effect: F: 2.456 p: 0.117 Interaction task X system: Not significant
	Y	Left	Not included in this research
		Right	System effect: F: 9.191 p: 0.002 Interaction task X system: F: 4.170 p: 0.041

Table 3
SPSS Post hoc analysis interaction effect. (α = 0.025)

Joint	*Coordinate*	*Task*	*Statistical Outcome*
Knee Right	Y	Walk	System effect: F: 0.810 p: 0.368
		Jog	System effect: F: 7.988 p: 0.005

4.2.2 SPM

SPM graphics can be viewed in figure 5-14. The dotted red line corresponds to the p-value of 0.05 for the main effects and 0.025 for post-hoc analysis.

4.2.2.1 System comparison

X-axis

For the X-axis coordinates, there was a significant difference between the systems for the right elbow joint centre during the entire gait cycle, except from heel-off to toe-off (p:0.031-0.033). There was a significant difference in elbow joint centre coordinates between the systems at initial-contact (p: 0.048), the transition between loading-response and mid-stance (p: 0.050), the transition between mid-stance and terminal-stance (p: 0.048) and throughout the swing-phase (p: 0.022). From initial contact to the end of the mid-stance, the right knee showed a significant difference between the manual annotation and markerless motion capture software (p: 0.001). Halfway through the terminal stance until the end of the swing-phase the data showed to be significantly different between the two systems (p: 0.001). The tracking of the joint-centres on the X-axis had a significant difference between Kinovea and DLC for both the left knee and hip, all the way through the gait-cycle (p: 0.001).

Y-axis

For tracking coordinates of joint centres along the Y-axis of the right elbow, there was only a significant difference between the two systems from the mid-stance to halfway through the terminal-stance (p: 0.031) and during the first half of the swing-phase (p: 0.026). The right knee showed a significant difference between the systems all the way through terminal stance (p: 0.001) and during the final part of the swing-phase (p: 0.001). The tracking of the left hip joint centre was significantly different between the two systems for the full stride ($p < 0.001$).

4.2.2.2 Interactions

Since there were some significant interactions between the systems and the task executed by the participants, post hoc analyses were done for right elbow Y-coordinates, right knee Y-coordinates and left hip Y-coordinates. In the post hoc analyses of the right elbow Y-coordinates significant differences can be observed from halfway through the terminal-stance to the first part of the swing-phase during walking (p: 0.001). During jogging, there were significant differences at initial contact (p: 0.002) and at the end of the swing-phase (p: 0.008). Significant differences were also found at the middle part of the swing-phase (p: 0.001). Post hoc analysis of the right knee Y-coordinates show significant differences at the start of terminal stance during walking (p: 0.004), as well as during the terminal-stance, pre-swing and the final part of the swing-phase during jogging (p: 0.001). In the post hoc analyses of the left hip Y-coordinates significant between-system differences were found through the whole gait cycle for both walking and jogging (p:0.001).

Figure 5
SPM Graph. Right Elbow X-axis

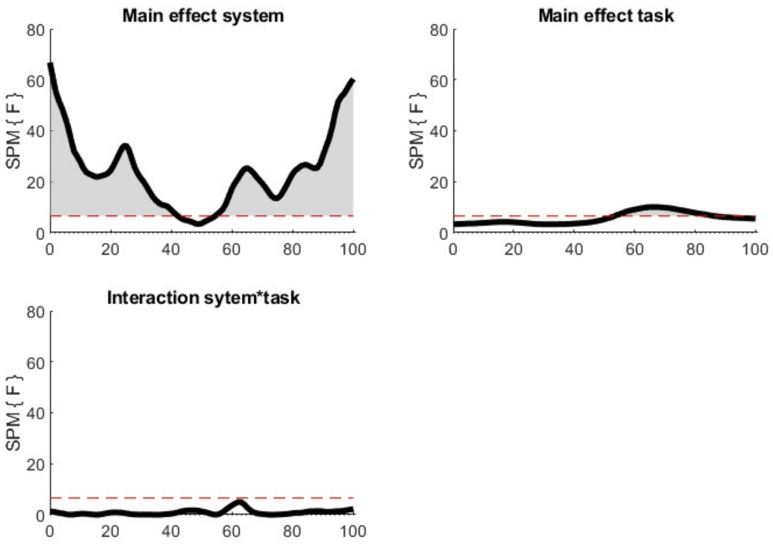


Figure 6
SPM Graph. Right Elbow Y-axis

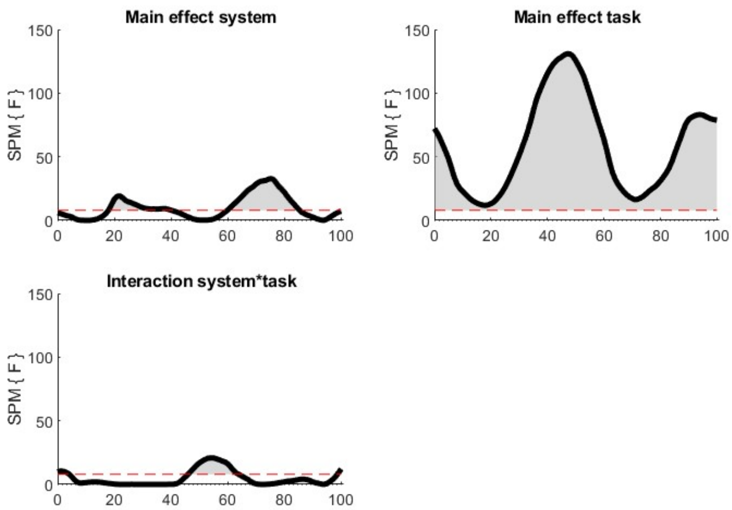


Figure 7
SPM Graph. Left Elbow X-axis

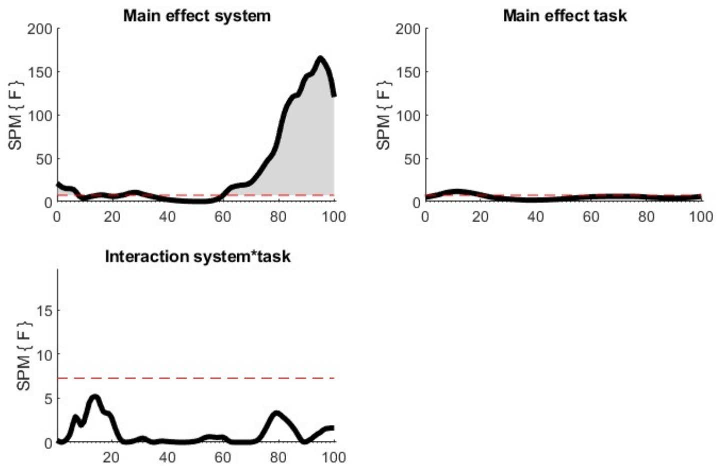


Figure 8
SPM Graph. Right Knee X-axis

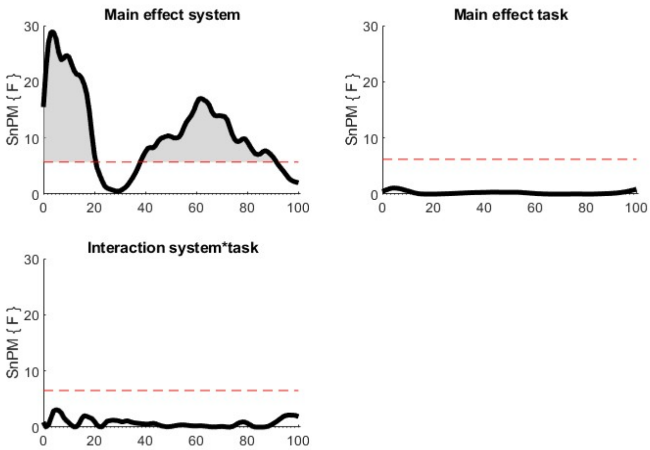


Figure 9
SPM Graph. Right Knee Y-axis

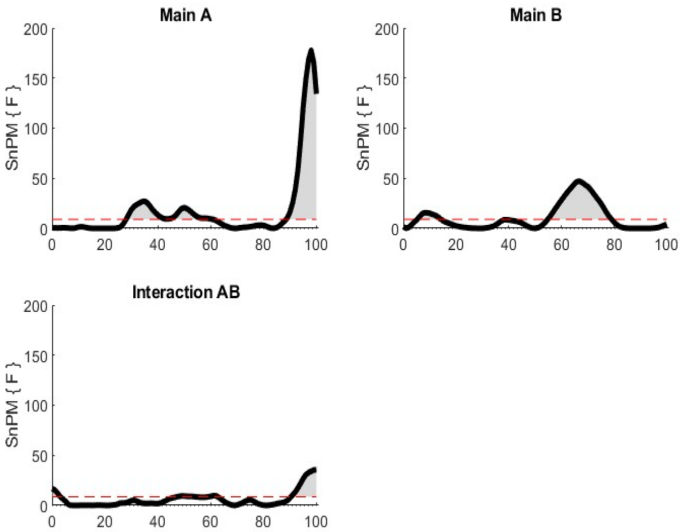


Figure 10
SPM Graph. Left Knee X-axis

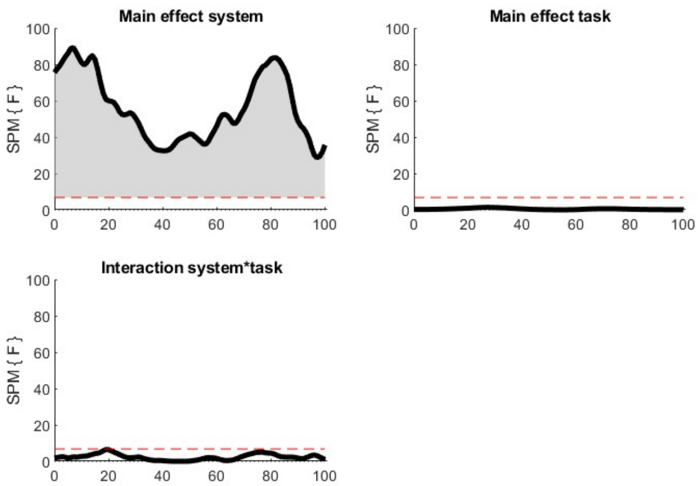


Figure 11
SPM Graph. Left Hip Y-axis

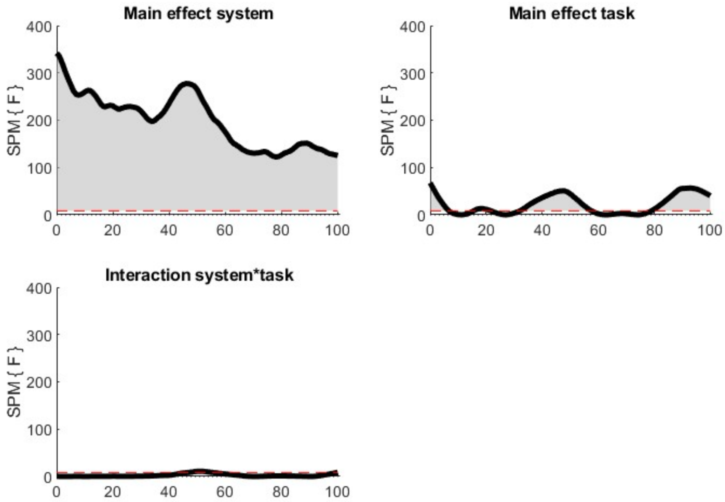


Figure 12
SPM Graph. Right Elbow Post Hoc Analysis Y-axis

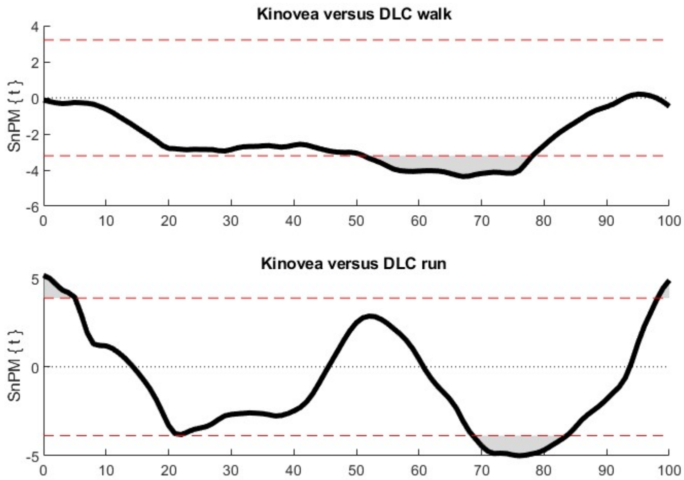


Figure 13
SPM Graph. Right Knee Post Hoc Analysis Y-axis

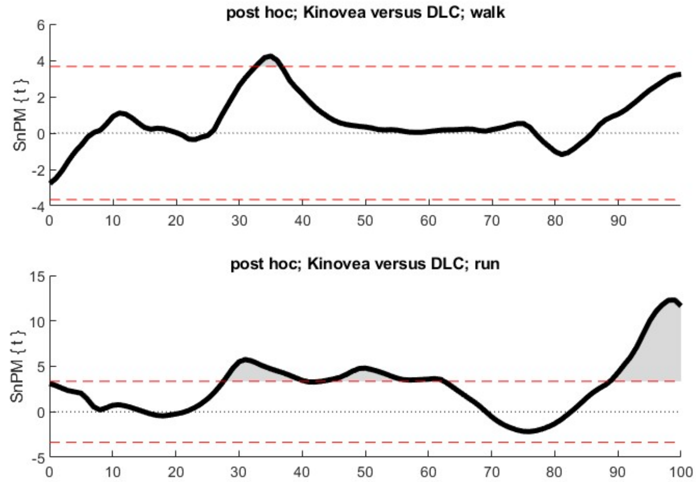
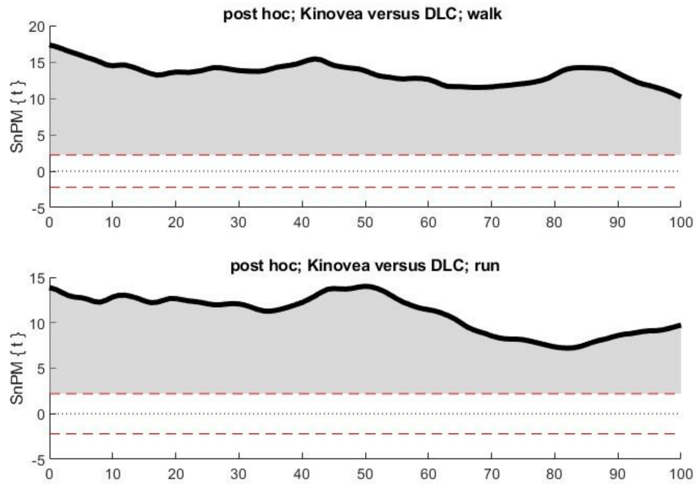


Figure 14
SPM Graph. Left Hip Post Hoc Analysis Y-axis



5 Discussion

We aimed to assess the validity of DeepLabCut for frontal plane joint centre tracking during walking and jogging with respect to Kinovea. Our hypothesis that DLC is valid for tracking joint centres in the frontal plane when compared to Kinovea was rejected as there were few non-significant differences found.

5.1 Results

Overall, the results show that there are many significant differences between DeepLabCut and manual annotation in Kinovea when tracking joint centres. Since there are to our knowledge no studies on the validity of DLC for estimating joint centres in the frontal plane, it is difficult to compare our results to those of other studies. However Washabaugh et al. (2022)[25] reported that DLC misplaced knee joint centres in the sagittal plane during the swing phase of gait. This corresponds with our findings, but since this study analysed kinematic data in the sagittal plane further research in the frontal is necessary to completely confirm these findings. In our study there were no joints for which the results showed a non-significant difference on both X- and Y-axis coordinates during the full stride length. The left hip joint tracking was significantly different between both systems during the entire stride length. The cause of this may be the fact that the participants were obligated to wear a dark top and dark pair of shorts during the trials. This made for a difficult distinction between upper and lower body on the video recordings. A better resolution might positively affect this problem, but further research is necessary to confirm this. Next the annotation for the training of the markerless model and the annotation in Kinovea was done by different persons. This may cause differences in the final joint centre tracking data as well. As stated by Needham et al. (2021)[17], lightning may influence the performance of markerless motion capture software and manual annotation because of possible noise in the form of motion blur. This can be a possible explanation for differences in the accuracy of tracking the X-coordinates of the left and right elbow and knee, since the floodlight used during data collection was only present on the left side of the subject. 40% to 100% of the stride contained significant differences for all joints included in this research according to the SPM analysis. In our opinion this is not accurate enough to be used in a practical setting. Cronin et al. (2019)[6] observed that training a model with more images can positively affect the performance of markerless motion capture for tracking joint centres in the sagittal plane during underwater running. They found that 300 images was sufficient for the underwater task. There were no references found for jogging and walking in the frontal plane, but further training of the MPII human model could enhance the performance of DLC to estimate joint centres in this situation.

When comparing the results from SPM and SPSS to each other different results were found for the X-axis values of the joint centres of the right knee and elbow. A possible explanation can be found in the fact that stride data was time-normalised for SPM analysis but not for the analysis in SPSS. Furthermore SPM analysis shows the differences between the systems and tasks throughout the different stages of the gait cycle while SPSS output shows a global result of the entire gait cycle.

When comparing the results during walking and running more differences are found for Y-axis coordinates. A possible explanation could be the increased vertical displacement of the joints during running in comparison to walking. This increased displacement could possibly cause greater errors in tracking joint centres. The SPM output also shows greater differences between the systems during phases of the gait cycle where joint displacement is greater.

5.2 Strengths and limitations

This study compared markerless motion capture with manual annotation of joint centres. To our knowledge this is the first study about the validity of joint centre tracking using DeepLabCut in the frontal plane during walking and jogging. A new protocol had to be set up from the start. Difficulties were encountered during this process, which may have had an impact on the results of this study. One of the technical difficulties was the low frame-rate of the video recordings caused motion blur. To improve this a floodlight was used but this was only possible on one side of the experimental setup. In the future two floodlights could be used, one on each side of the experimental set up, to make sure there are no differences in lighting on both sides of the subject. 25 fps was the maximum frame rate of the cameras used in this protocol. A higher frame rate might positively affect the accuracy of the systems, but this should be confirmed in further research. Also the resolution of the video recordings were not in full high-definition, which may interfere with the accuracy of manual annotation in

Kinovea. The accuracy of manual annotation also depends on the capability of the person who annotates the joint centres. This might have influenced the results found in this study since manual annotation was done by two independent researchers. Comparing with a marker-based method might be a solution for this problem. But physical markers can interfere with the training of the markerless algorithm, since there would be a high risk of the algorithm learning to identify the markers[6]. A strength of this study can be found in the synchronisation of the steps with the GaitRite system and normalising the data for the statistical analysis, making it possible to interpret results for different stages of the gait cycle. Lastly, the small sample size should be mentioned. Only twenty participants were included in this study, since it is a part of a larger study that will be conducted over the course of the following years. More data on this topic will be acquired via the same protocol, making it possible to easily follow up on the progress of technology and possibly confirm our results in the future.

6 Conclusion

For tracking joint centres during gait in the frontal plane, DeepLabCut is not valid in comparison to manual annotation. Further research is recommended to improve the accuracy of deep learning software to recognise joint centres in images and to improve its validity for tracking joint centres in the frontal plane.

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8 Attachments