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# Validity of Neural Networks to Determine Body Position on the Bicycle

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**ABSTRACT**

**Purpose:** With the increased access to neural networks trained to estimate body segments from images and videos, this study assessed the validity of some of these networks in enabling the assessment of body position on the bicycle. **Methods:** Fourteen cyclists pedaled stationarily in one session on their own bicycles while video was recorded from their sagittal plane. Reflective markers attached to key bony landmarks were used to manually digitize joint angles at two positions of the crank (3 o'clock and 6 o'clock) extracted from the videos (Reference method). These angles were compared to measurements taken from videos generated by two deep learning-based approaches designed to automatically estimate human joints (Microsoft Research Asia-MSRA and OpenPose). **Results:** Mean bias for OpenPose ranged between 0.03° and 1.81°, while the MSRA method presented errors between 2.29° and 12.15°. Correlation coefficients were stronger for OpenPose than for the MSRA method in relation to the Reference method for the torso ($r$ = 0.94 vs. 0.92), hip ($r$ = 0.69 vs. 0.60), knee ($r$ = 0.80 vs. 0.71), and ankle ($r$ = 0.23 vs. 0.20). **Conclusion:** OpenPose presented better accuracy than the MSRA method in determining body position on the bicycle, but both methods seem comparable in assessing implications from changes in bicycle configuration.

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Biomechanics; kinesiology; quantitative study; technology

Bicycle fitting is a method utilized to optimize the position of the bicycle to the cyclist (Bini, Hume, & Croft, 2014), which involves a range of measurements to assess cyclists' posture on their bicycles. Among the most recommended techniques to assess body position on the bicycle, analysis of joint angles from video recording has been largely used as it allows for bicycle fitting to be further individualized (Fonda et al., 2014; Swart & Holliday, 2019). However, accurate measurements of angles involve determining joint centers from manual palpation and markup of bony landmarks on the skin (Malus et al., 2021), which can be prone to errors depending on the experience of the assessor (Sinclair et al., 2014). Nevertheless, whenever markers are properly attached to bony landmarks, they are considered a gold standard method.

The use of marker-less methods to extract joint centers from video has been attempted in several studies (Grigg et al., 2018; Needham et al., 2017; Ong et al., 2017; Serrancolí et al., 2020). Ong et al. (2017) observed differences of <1° for various joint angles using a marker-less tracking system during walking and jogging, demonstrating promising outcomes. More recently, the use of convolutional neural networks (CNNs) trained on large image datasets (Cao et al., 2021) improved human pose estimation and joint center identification. These methods involve the use of images from people performing various movements (i.e., walking, jumping, dancing, etc.) that are labeled to determine body segments and joints (i.e., keypoints) and used for training a computer program to automatically identify similar patterns in new images. However, only Serrancolí et al. (2020) utilized CNN-based approaches to identify segmental movement and joint centers during cycling.

This application is important as it can further allow for marker-less methods to determine cyclists' position on the bicycle and potentially inform bicycle fitting. However, comparison with criterion methods (i.e., marker-based) is lacking given neural networks use different assumptions in determining joint centers (i.e., methods to determine body segments). This provides an opportunity to utilize pre-trained networks that can determine human body segments and joints for the analysis of cycling.

Body position on the bicycle has largely involved determining upper and lower limb angles at key parts of the crank cycle. As an example, the 6 o'clock (Bini, 2020; Peveler & Green, 2011; Priego Quesada et al., 2016) and the 3 o'clock positions of the crank cycle (Bini & Hume, 2016; Bini, Hume, Croft, & Kilding, 2014) were utilized. The main rationale for choosing these positions is because the 6 o'clock is close to the maximum extension of the lower limbs (Holmes et al., 1994) and the 3 o'clock is close to the peak pedal power (Martin & Brown, 2009). Therefore, examining joint angles at these positions can help differentiate cycling posture (Bini, Hume, Croft, & Kilding, 2014). However, the use of marker-less motion analysis methods has not been assessed in terms of their accuracy in determining cyclists' posture. The use of marker-less method as part of bicycle fitting assessment using video-calls can be helpful because the restrictions from COVID-19 have limited face-to-face non-essential activities globally. Moreover, utilizing freely available pre-trained networks could accelerate the use of these automated methods by practitioners, reducing barriers such as image labeling and network retraining.

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Therefore, the aim of this study was to compare a marker-based method for estimating joint angles on the bicycle (i.e., Reference) with two open-source convolutional neural networks (Cao et al., 2021; Xiao et al., 2018) designed to perform the same task automatically. Given that these pre-trained networks are normally trained using images from people performing a wide range of movements (e.g., walking, jumping, dancing, etc.), our hypothesis was that both methods should provide practically acceptable measurements of body position on the bicycle (i.e., joint angles). Therefore, broad learning obtained from both networks should be appropriate to detect body segments in cycling-related images.

## Materials and methods

Fourteen male cyclists (33 ± 7 years of age, 176 ± 6 cm of stature, and 74 ± 8 kg of body mass) ranging from recreational to competitive were assessed in a single session using their own bicycles (road, triathlon, or mountain bike). They were engaged in road, triathlon, or mountain bike training covering 5 ± 3 hr and 128 ± 65 km of cycling training per week at the time of the study. We based our sample size calculation on the intention to determine a minimum difference of 5° in angles, which is at the center of the range proposed to determine body position on the bicycle (i.e., 10°; Millour et al., 2019; Swart & Holliday, 2019). We also assumed that the within-cyclist's variability in angles would be 3.4° (Bini & Hume, 2016), resulting in an effect size of 1.47. Our sample size calculation involved a comparison of paired samples when $\alpha = 0.05$ and the power of the test is 0.80 using G*Power statistical package (Faul et al., 2007). Before data collection, all cyclists signed an informed consent to participate in the study, which was approved by the University Human Ethics Committee (HEC19001).

After measurements of stature and body mass, cyclists performed 2 min of cycling on their own bicycles attached to a home cycle trainer (Active Intent Fitness Bike Trainer, NZ) at self-selected cadence. A high-speed camera (Exilim EX-FC150, Casio Computer CO, Tokyo, Japan) was positioned at the height of their saddle, 4-m away from the bicycles to record movement in the sagittal plane. Reflective markers were positioned at the acromion, greater trochanter, lateral femoral epicondyle, lateral malleolus, and the head of the fifth metatarsal bone (Figure 1). Videos were recorded for 20 s at the end of the 2 min of exercise at 120 fps (640 × 480 of frame resolution) using automated quick shutter and anti-shake settings to minimize blur.

In this study, we compared the OpenPose (bottom-up) and the Microsoft Research Asia (MSRA—top-down) methods, deep learning-based approach designed to estimate human pose and joint angles, in the context of bicycle fitting. The bottom-up method relies on existing data to train the network,

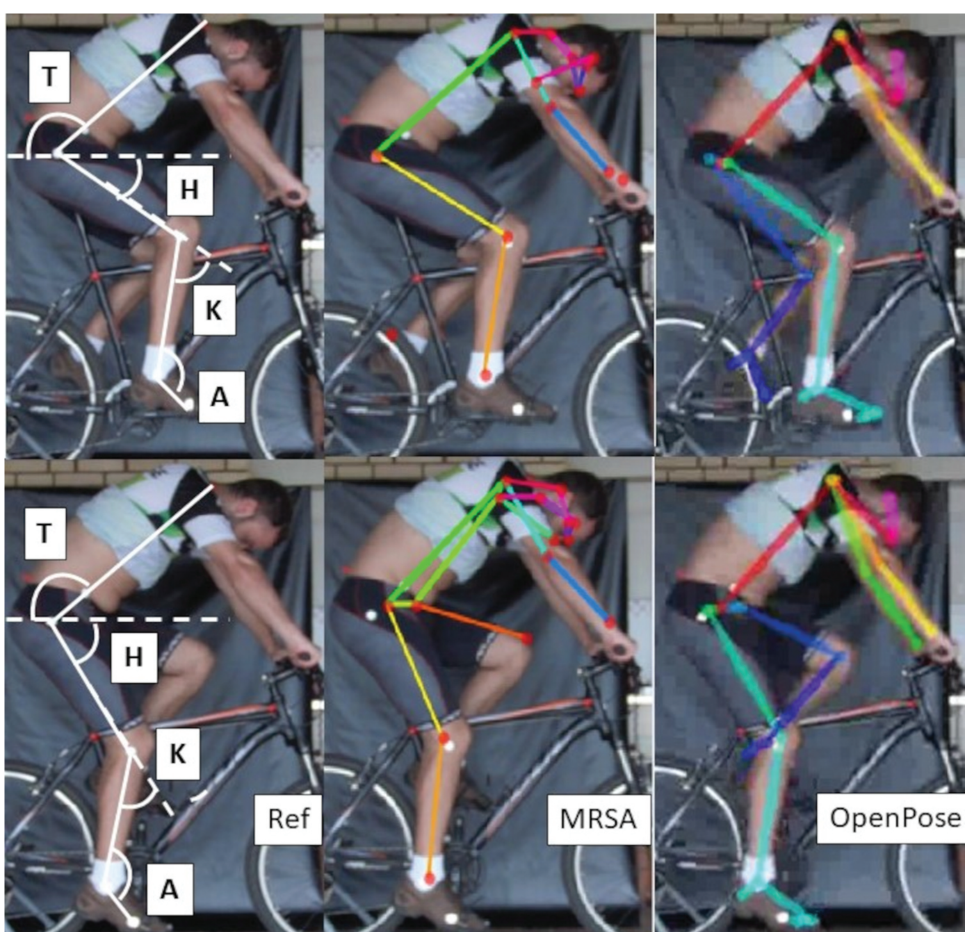


**Figure 1.** Illustration of the measured angles and image from the skeleton created by the MSRA method.

while the top-down method uses current learning to improve the accuracy of the network in future predictions. The MSRA method first detects the location of people in an image and then the body segments for each detected person. Individuals and their respective body segments are detected using the Mask RCNN framework (He et al., 2020), which is a two-stage approach where, in the first stage, images are scanned to determine areas likely to contain an object, while the second stage classifies these areas and generates bounding boxes and masks (i.e., removing surroundings). To associate each person and its body segments with detections from consecutive frames, the authors proposed a tracking algorithm that takes advantage of temporal information via optical flow technique (Teed & Deng, 2020). This involves extrapolating future position of segments during sequential movement from historical data (i.e., bottom-up approach). OpenPose introduced the concept of association scores via Part Affinity Fields (PAFs), which are a set of vector fields that determine the location and orientation of body segments. The vector fields allow the estimation of a degree of association between body segments. OpenPose computes a confidence map that informs the location of the body segments and a set of vector fields (PAFs). Finally, both the confidence map and PAFs are fused by a greedy inference strategy to estimate the final set of joints (i.e., optimization of joint locations), for each person in the image.

Video files were then imported into a customized program adapted from a freely available code. This code implements the Microsoft Research Asia (MSRA) method (Xiao et al., 2018) in MATLAB (R2021a, MathWorks Inc., Natick, MA, USA). In this study, we used a model pre-trained in the COCO Consortium (cocodataset.org; Lin et al., 2014), which involves annotation of 250,000 people with segments identified in a broad range of movements such as walking, jumping, and dancing, as examples. Video files were generated where the joint centers (i.e., keypoints) and body segments were identified by the pre-trained neural network. The same process was conducted using the OpenPose method (Cao et al., 2021), which is also pre-trained in the COCO dataset. Videos generated by the MSRA and the OpenPose methods were later utilized to manually digitize torso, hip, knee, and ankle angles in two parts of the crank cycle (3 o'clock and 6 o'clock), as shown in Figure 1. As a reference method, videos with only reflective markers were utilized. Raw videos (i.e., Reference method) and pre-trained neural network-generated videos were imported into ImageJ (National Institutes of Health, USA), where a single experienced assessor measured the angles across five consecutive cycles. Even though both pre-trained neural networks estimated joint coordinates, we followed a method utilized in clinics and bike fitting, where angles are manually measured from pre-located joint positions on the video (e.g., Bike Fast Fit —Video Bike Fitting). This process enables the identification of angles in key areas of the crank cycle without a requirement of tracking multiple video frames. Because the MRSA did not track the foot, the ankle angle was measured using the head of the fifth metatarsal bone marker for all methods.

Differences in mean angles from each cyclist between manually placed markers and joint position predicted by the neural network methods in relation to the Reference method were determined using paired-samples $t$-tests for each crank position. Magnitude of differences was assessed using Cohen's effect sizes ($d$). Whenever $p < .05$ and $d > 0.80$, practically important differences were assumed from the data. Mean bias and confidence interval for the differences (CI95) were calculated as part of the Bland–Altman method (Martin Bland & Altman, 1986), and Pearson correlations were computed to assess association between methods. $R$ values were ranked as poor (0–0.5), moderate (0.5–0.75), good (0.75–0.90), and excellent (>0.9; Dancey & Reidy, 2004). Statistical analyses were conducted using customized spreadsheets (Excel, Microsoft Inc., USA) and GraphPad Prism (Version 9.0.2, GraphPad Software, San Diego, CA, USA).

## Results

Significant differences were observed between angles from the MSRA method in comparison to the Reference method, at the 3 o'clock crank position, for the torso ($p < .01$, $d = 0.38$), hip ($p < .01$, $d = 1.93$), knee ($p < .01$, $d = 1.52$), and ankle ($p = .01$, $d = 1.05$). No differences though were observed between angles from the OpenPose and the Reference method (torso $p = .09$, hip $p = .12$, knee $p = .69$, and ankle $p = .36$). Angular data are presented in Table 1.

Mean bias [CI95] between angles from the MSRA method compared to the Reference method at the 3 o'clock position was −2.6° [−8.0; 2.8] for the torso, 8.9° [0.8; 16.9] for the hip, 12.1° [−0.3; 24.6] for the knee, and 7.8° [−11.3; 26.9] for the ankle. Mean bias [CI95] between angles from the OpenPose method in comparison to the Reference method at the 3 o'clock position was 1.5° [−4.6; 7.6] for the torso, 1.4° [−4.9; 7.8] for the hip, 0.4° [−7.7; 8.6] for the knee, and −1.5° [−13.3; 10.2] for the ankle. Correlation coefficients were stronger for the OpenPose method than for the MSRA method in relation to the Reference method for the torso ($r = 0.94$ vs. 0.92—excellent), hip ($r = 0.69$ vs. 0.60—moderate), knee ($r = 0.80$—good vs. 0.71—moderate), and ankle ($r = 0.23$ vs. 0.20—poor). Bland–Altman plots illustrate these outcomes in Figure 2.

Significant differences were observed between angles from the MSRA method in comparison to the Reference method, at the 6 o'clock crank position, for the torso ($p < .01$, $d = 0.67$), hip ($p = .01$, $d = 0.52$), and knee ($p = .02$, $d = 0.46$). No differences were observed for the ankle ($p = .10$). No differences were observed between angles from the OpenPose method and the Reference method (torso $p = .08$, hip $p = .97$, knee $p = .09$, and ankle $p = .28$). Angular data are presented in Table 1.

**Table 1.** Mean ± SD angles of the torso, hip, knee, and ankle at the 3 o'clock and 6 o'clock crank positions determined using the reference method, the MSRA method, and the OpenPose method.

| Angles (°) | Torso | Hip | Knee | Ankle |
|---|---|---|---|---|
| **3 o'clock crank position** | | | | |
| Reference | 137 ± 7 | 41 ± 4 | 63 ± 7 | 120 ± 6 |
| MSRA | 139 ± 7* | 32 ± 5* | 75 ± 9* | 113 ± 9* |
| OpenPose | 135 ± 9 | 40 ± 3 | 64 ± 5 | 122 ± 3 |
| **6 o'clock crank position** | | | | |
| Reference | 136 ± 7 | 68 ± 4 | 33 ± 8 | 140 ± 8 |
| MSRA | 141 ± 7* | 65 ± 5* | 37 ± 11* | 137 ± 11 |
| OpenPose | 134 ± 9 | 68 ± 4 | 35 ± 7 | 141 ± 8 |

*Indicates significant difference in relation to the Reference method.

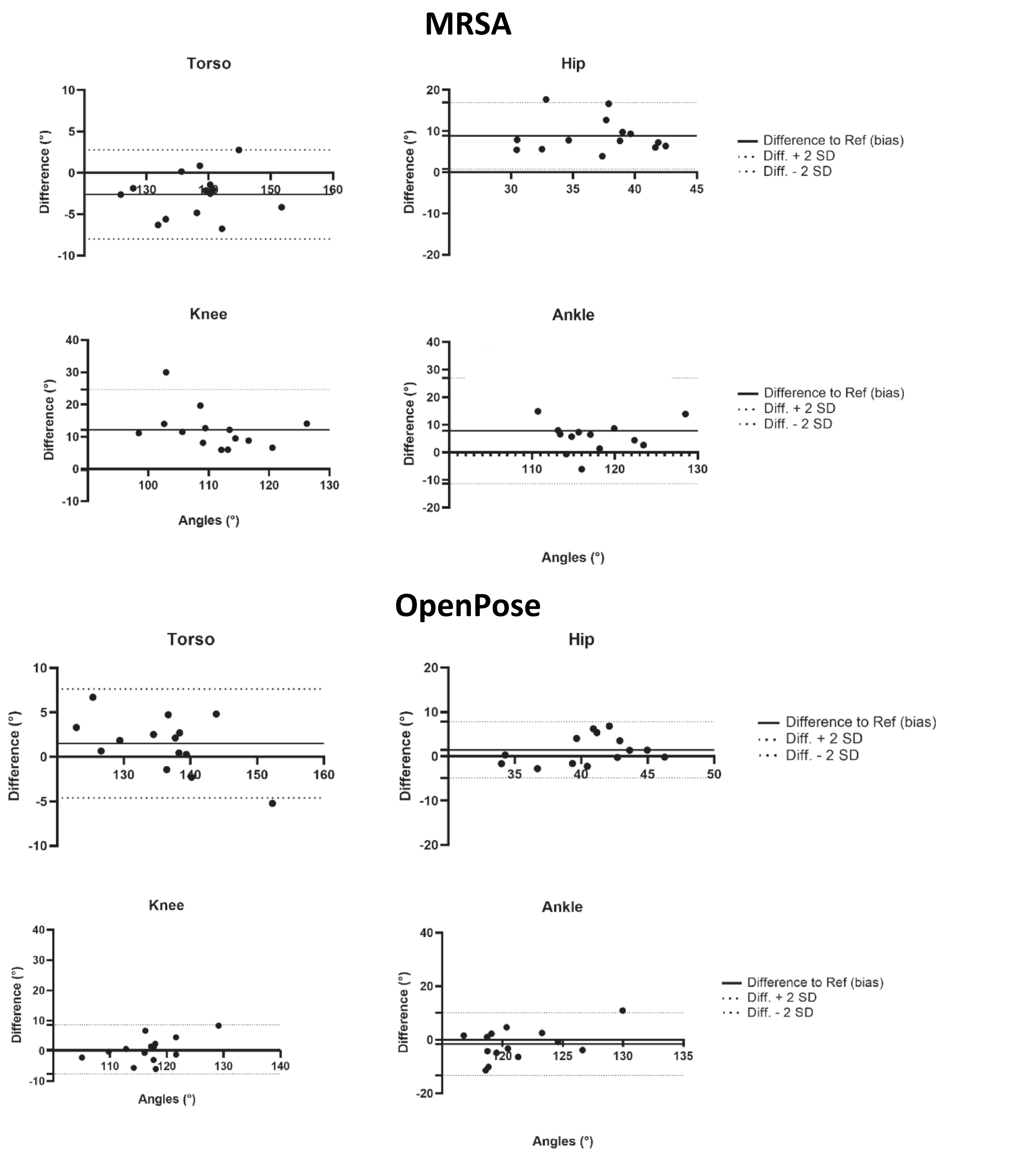


**Figure 2.** Bland–Altman plots comparing differences, mean bias (continuous lines), and limits of agreement (dotted lines) between the MSRA method and the Reference method (Ref—upper panel) and the OpenPose method and the Reference method (lower panel) for the 3 o'clock crank position.

Mean bias [CI95] between angles from the MSRA method in comparison to the Reference method at the 6 o'clock position was −4.4° [−12.8; 3.9] for the torso, 2.3° [−2.9; 7.5] for the hip, 4.3° [−7.7; 16.3] for the knee, and 3.3° [−10.7; 17.4] for the ankle. Mean bias [CI95] between angles from the OpenPose method in comparison to the Reference method at the 6 o'clock position was 1.81° [−5.1; 8.7] for the torso, −0.1° [−4.3; 4.3] for the hip, 1.5° [−4.8; 8.0] for the knee, and −1.2° [−9.1; 6.7] for the ankle. Correlation coefficients were stronger for the OpenPose method than for the MSRA method in relation to the Reference method for the torso ($r$ = 0.94—excellent vs. 0.79—good), hip ($r$ = 0.86 vs. 0.82—good), knee ($r$ = 0.91—excellent vs. 0.82—good), and ankle ($r$ = 0.87 vs. 0.75—good). Bland–Altman plots illustrate these outcomes in Figure 3.

## Discussion

The purpose of this study was to compare joint angles on the bicycle assessed using pre-trained neural networks with outputs from a marker-based method. The hypothesis was that both methods would provide practically acceptable measurements of joint angles due to similarities in body position. The

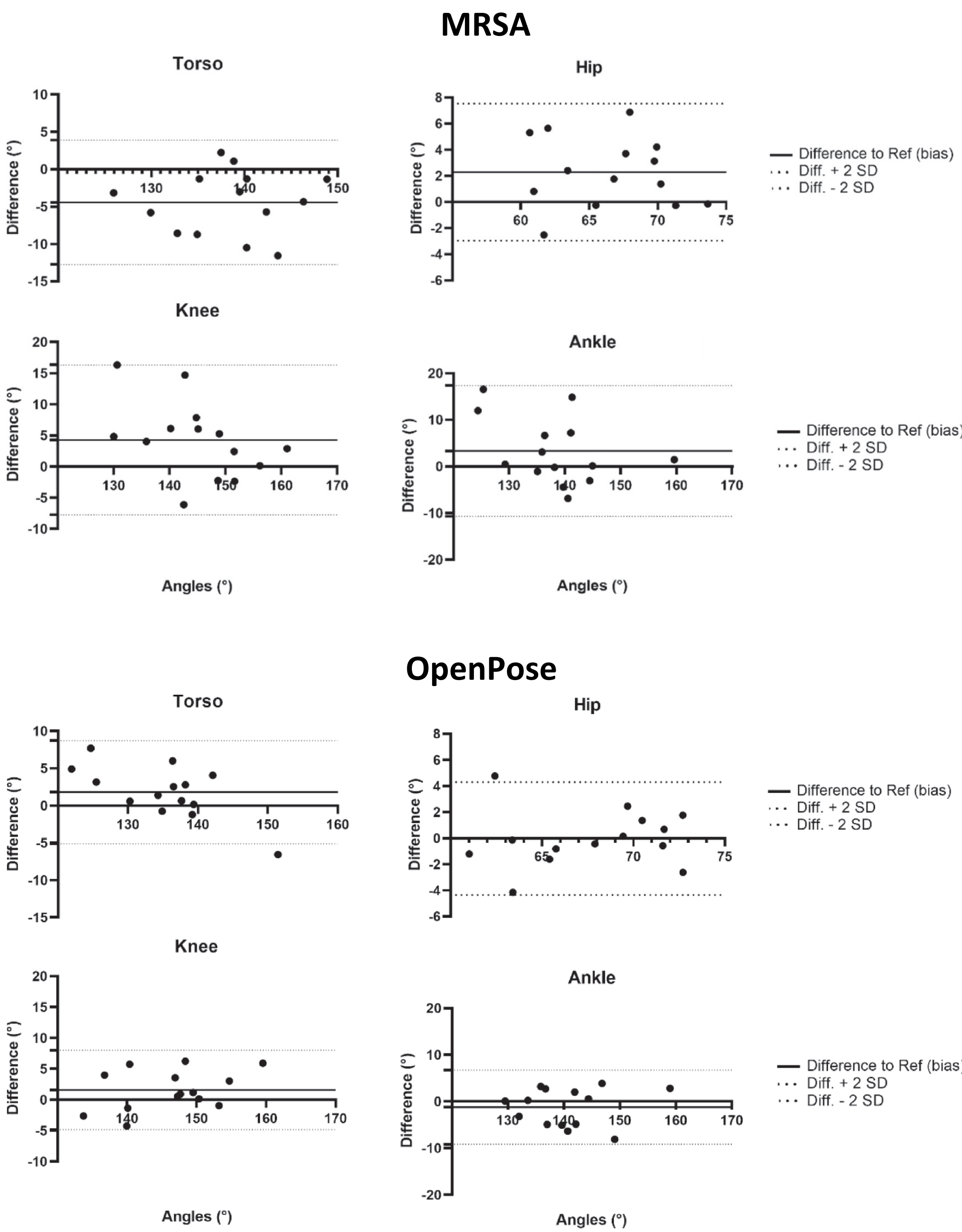


**Figure 3.** Bland–Altman plots comparing differences, mean bias (continuous lines), and limits of agreement (dotted lines) between the MSRA method and the Reference method (Ref—upper panel) and the OpenPose method and the Reference method (lower panel) for the 6 o'clock crank position.

data demonstrated that the OpenPose method presented greater accuracy than the MSRA method in determining body position on the bicycle. Mean bias for the OpenPose method ranged between 0.03° and 1.81°, while the MSRA method presented errors between 2.29° and 12.15°. Ong et al. (2017) observed differences of <1° for various joint angles using a marker-less tracking system during walking and jogging. During cycling, intra-session errors in joint angles have been shown to vary between <1° and 3° (Bini & Hume, 2020), which suggests that differences between the OpenPose method could be negligible but the MSRA method presented larger errors. These findings are novel because they demonstrate that an automated marker-less method (i.e., OpenPose) can accurately determine joint angles and help assess body position on the bicycle.

The assessment of joint angles during bicycle fitting is based on the fact that changes in bicycle configuration affect movement patterns (Bini, Hume, & Kilding, 2014; Menard et al., 2020). This means that accuracy in determining joint angles is important to ensure that the position of the cyclist on the bicycle aligns with the intention of the fitting process. On the other hand, changes in joint angles of ~10–14° when saddle position is modified have not been associated with changes in internal forces (Bini & Hume, 2014). This indicates that errors in determining knee angles may not result in large differences in bicycle configuration. It is also possible that errors in determining bicycle configuration (e.g., using the MSRA method) may not result in differences in perceived comfort (Bini, 2020; Priego Quesada et al., 2016). We can also speculate that these errors may only affect internal forces in parts of the crank cycle where joint loads are low (Bini, 2021). Therefore, further studies are needed to explore the implications of determining saddle position, for example, using automated marker-less methods. This is particularly important in light of the poor correlation between both methods and the Reference method for the ankle joint at the 3 o'clock position.

In this study, joint angles were measured in two key positions of the crank cycle, which limits the conclusion on whether automated methods can accurately track motion. It is possible that, in some parts of the crank cycle, errors in identifying body segments may be larger. As an example, the 3 o'clock position presented larger errors than the 6 o'clock position for the MSRA method, which can be potentially associated with the right and left limbs having a very distinct position at the 6 o'clock but a more similar position at the 3 o'clock, leading the automated method to swap sides of the skeleton. This though was not the case for the OpenPose method as errors were not largely different between crank positions. As neural networks are normally trained using a broad range of images or people moving (i.e., walking, jumping, dancing, etc.), the straight leg observed at the 6 o'clock potentially increases the accuracy of the networks to determine the skeleton. Therefore, training neural networks with cycling-related images is important to further enhance the accuracy of the network, particularly when using data to determine joint loads.

It is important to note that both CNN-based methods were designed considering largely non-cycling-related scenarios since they were based on COCO and MPII datasets. According to Cao et al. (2021), the MSRA method outperformed the OpenPose in 12.3 percentual points, considering the test set of the COCO dataset. However, our study demonstrates that OpenPose outperformed MSRA when using cycling-related images. The MRSA network has been trained to analyze images with a resolution of 256 × 192 pixels, while the OpenPose network used the whole image resolution. This means that OpenPose had increased resolution at each frame to determine joint keypoints, potentially explaining its increased accuracy. Our results suggest that the vector fields (PAFs), which encode the location and orientation of body segments, were more effective in determining the segments of a person in cycling-related images than the optical flow-based approach used in the MSRA method. This means that when using optical flow to determine sequential movement, the MSRA presented lower capacity than the OpenPose method to determine the joints. We believe that these results are valuable for computer scientists and engineers when designing AI-based methods for detecting human pose and joints. The use of the OpenPose to inform bicycle fitting provides an opportunity to streamline the analysis of posture on the bicycle and automate the extraction of quantitative outcomes (i.e., joint angles).

The use of a two-dimensional model is a very popular method of obtaining angles from cyclists in clinical and sports settings due to the easy access to video recording capability through smartphones. However, it is known that two-dimensional data presented ~2.2–10° of error in relation to three-dimensional data (Fonda et al., 2014; Umberger & Martin, 2001). Therefore, it is important that, if automated methods are used, errors in determining joint angles via two-dimensional analysis do not further increase the known limitations of sagittal plane analyses. Further studies should explore if the use of three-dimensional marker-less methods is feasible to analyze cycling motion, as they showed promising results in other movements (D'Antonio et al., 2021; Kanko et al., 2021).

Angles presented in this study were manually digitized from the video footage, which may add errors to the true measurement of joint angles. However, this element has been shown to increase to a trivial magnitude (i.e., <1.5°) bias in measuring joint angles in cyclists (Bini & Hume, 2016) and should be equivalent between methods as all involved manual digitization of angles. Therefore, future studies should compare intra-cycle data between methods to assess the extent of differences. It is also important to note that cyclists pedaled at self-selected sub-maximal intensity and cadence, which limits the assumption that the automated methods will perform similarly during higher intensity cycling (e.g., sprinting). Clean background was used, but it is unclear if the automated method would cope with data obtained in outdoor settings. Moreover, the use of online technology to assess cyclists remotely (e.g., Zoom, Gmeet, etc.) can facilitate bicycle fitting to be conducted via distance, but it is unclear if elements such as background and position and orientation of the camera would affect the accuracy of the automated methods. Videos from this study were collected with standard (640 × 480 pixels) frame resolution at high frame rate (120 fps), which is limited compared to some modern cameras. While some smartphones enable slow motion (i.e., high frame rate) to be recorded in high resolution, webcams are limited to 60 fps, with unclear implications on the performance of the automated methods. Therefore, future studies should explore changing camera settings in order to assess if outcomes from the automated method remain appropriate.

The use of publicly available codes to automate human pose estimation was also implemented in this study without changes to the original code. One improvement that should be attempted in future use involves filtering and interpolating the joint coordinates as noise was visually observed in the videos leading the automated methods to misinterpret the location of joint centers. These corrections have been utilized in prior research (Serrancolí et al., 2020) and should improve the quality of the data, particularly when temporal patterns are explored. In addition, exploring the accuracy of these networks when videos are recorded at lower frame rate and/or with less image resolution should benefit further use of these methods.

The conclusion is that the OpenPose method presented improved accuracy compared to the MSRA method in determining body position on the bicycle, but both methods seem feasible to assess implications from changes in bicycle configuration. The OpenPose method though should be preferably used when higher accuracy in determining joint angles is required.

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## Disclosure statement

No potential conflict of interest was reported by the author(s).

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