ASSESSMENT OF A MARKERLESS MOTION TRACKING METHOD TO DETERMINE BODY POSITION ON THE BICYCLE

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This study compared body position on the bicycle using manual and automatically determined body segments during stationary cycling. High speed video (120 fps) was obtained from 14 cyclists using their own bikes on a stationary cycle trainer in a single session. Torso, hip, knee and ankle angles were measured in two positions of the crank (3 o'clock and 6 o'clock-dynamically) to determine body position on the bicycle. Significant differences (3-12°, d=0.38-1.92) were observed for all joints between the manual and automated method for both crank positions (except for the ankle at the 6 o'clock). Overall, the automated method overestimated torso and knee flexions and underestimated hip flexion and ankle dorsiflexion. Even though changes in angles were deemed meaningful, implications in terms of bicycle fitting are to be fully determined.

KEYWORDS: Artificial intelligence, bike fitting, movement analysis.

INTRODUCTION: The restrictions resulting from the COVID-19 pandemic have been limiting the work of clinicians in assessing athletes face-to-face in a number of countries. These limitations have affected the ability of bicycle fitters to support cyclists with service that could potentially prevent injuries (Estivalet, Brisson, Iriberri, Muriel, & Larrazabal, 2008; Fonda, Sarabon, & Li, 2014). Amongst the methods utilised for bicycle fitting, assessing body position on the bicycle using movement analysis technology has gained importance due to its potential to reduce fatigue and pain (Priego Quesada, Pérez-Soriano, Lucas-Cuevas, Salvador Palmer, & Cibrián Ortiz de Anda, 2016). As an alternative, videos taken remotely using online platforms (e.g. Zoom, Gmeet, etc.) could be used but it is not possible to manually mark-up cyclists' bony landmarks to determine angles. Therefore, the use of novel automated methods to determine joint centres from video files can be explored. Recent studies using markerless video recording demonstrated similarities with criterion marker-based systems or potential for use in the field (Grigg, Haakonssen, Rathbone, Orr, & Keogh, 2018; Needham, Long, & Irwin, 2017). However, none of these studies compared the similarities of joint angles obtained from automated methods with those obtained using manually marked landmarks. Moreover, trained artificial intelligence (AI) technology using machine learning and large datasets of images could potentially improve the accuracy of automated methods in identifying human body segments in video frames. Moreover, it will be possible to reduce time taken to analyse videos using an automated method with AI assistance. However, the implications of the use of automated methods in determining body position on the bicycle have not been explored. Therefore, the purpose of this study was to compare body position on the bicycle during cycling using manual vs an automated method to determine joint angles.

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. They were engaged in road and triathlon training covering 5±3 hours and 128±65 km of cycling training per week at the time of the study. 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, reflective markers were positioned by a single investigator at the acromion, greater trochanter, lateral femoral epicondyle, lateral malleolus and at the pedal spindle (Figure 1). Cyclists then performed 2-min of cycling in their own bicycles attached to a home 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 and lateral malleolus (Figure 1). Videos were recorded for 20-s at the end of the 2-min of exercise at 120 fps (640x480 of frame resolution).

Raw video files were imported to a customised program adapted from a shared code. This code uses a pre-trained network in MATLAB (R2021a, MathWorks Inc, Natick, MA, USA) in identifying human body segments from images available in the COCO Consortium (cocodataset.org). New video files were generated where the joint centres were identified by the pre-trained neural network, which were later utilised to manually digitise torso, hip, knee and ankle angles in two parts of the crank cycle (3 o'clock and 6 o'clock). Raw videos and videos generated by the neural network were imported to ImageJ (National Institute of Health, USA) where a single experienced assessor measured the angles manually across five consecutive cycles for each participant in both videos. Differences in mean angles from each cyclist between manually placed markers and joint centre predicted by the neural network (automated method) were determined using paired samples t-tests for each crank position. Magnitude of differences were assessed using Cohen's effect sizes (d). Whenever $p < 0.05$ and $d > 0.80$, practically important differences were assumed from the data. Statistical analyses were conducted using customised spreadsheets (Excel, Microsoft Inc, USA).

RESULTS: Angles of the torso, hip, knee and ankle joints are illustrated in Figure 1, along with results obtained by each method (manual vs. automated).

	3 o'clock	
Angles (°)	Manually marked	Automated method
Torso	137±7	139±7
Hip	41±4	33±5 *
Knee	63±7	76±9 *
Ankle	120±6	113±9 *

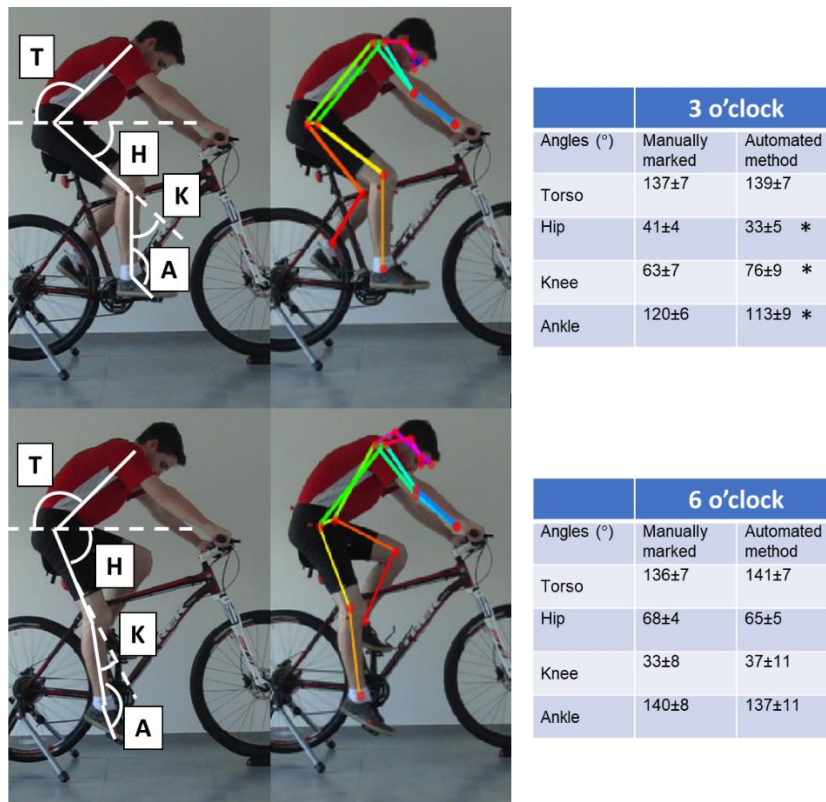|	6 o'clock	
Angles (°)	Manually marked	Automated method
Torso	136±7	141±7
Hip	68±4	65±5
Knee	33±8	37±11
Ankle	140±8	137±11

Figure 1. Illustration of the measured angles (torso-T, hip-H, knee-K and ankle-A) and data from each method (Manual-left and Automated-right). * Indicates practically important differences between methods.

At the 3 o'clock crank position, significant differences between methods were observed for the torso (~3°, p<0.01, d=0.38), hip (~9°, p<0.01, d=1.93), knee (~12°, p<0.01, d=1.52) and ankle (~8°, p=0.01, d=1.05). At the 6 o'clock crank position, the torso (~4°, p<0.01, d=0.67), the hip (~2°, p=0.01, d=0.52) and the knee (~4°, p=0.02, d=0.46) were different between methods, without differences for the ankle angle (~3°, p=0.10, d=0.35).

DISCUSSION: This study demonstrated that body position on the bicycle was significantly different when assessed from an automated method compared to a manual method of determining joint angles in cycling. Differences in joint angles ranged from 3-12° at the 3 o'clock crank position and 3-4° at the 6 o'clock crank positions. Ong et al. (2017) observed differences of <1° for various joint angles using a markerless tracking system during walking and jogging. During cycling, typical errors in joint angles intra-session have been shown to range between <1-3° (Bini & Hume, 2020), which suggest that differences between methods are mostly meaningful.

During bicycle fitting, changes in setup affect movement patterns, which can be determined via analysis of joint angles (Bini, Hume, & Kilding, 2014; Menard, Domalain, Decatoire, & Lacouture, 2020). Therefore, if angles cannot be identified properly, it is difficult to ensure that body position on the bicycle can be reliably determined. On the other hand, differences of less than ~10-14° were associated with no differences in knee forces when saddle position was changed (Bini & Hume, 2014), which suggest that errors in determining knee angles may not result in large differences in bicycle setup. It is possible though that, changes in bicycle setup from errors by the automated method may not result in differences in perceived comfort (Bini, 2020; Priego Quesada et al., 2016) or may only result in differences in joint angles in parts of the crank cycle where joint forces are low (Bini, 2021).

Only two positions of the crank cycle were explored in the current study, which limits the conclusion on whether the automated method can accurately track motion. It may be possible that, in some parts of the 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. One potential reason could be that right and left limbs have a very distinct position at the 6 o'clock but a more similar position at the 3 o'clock, which leads the automated method to swap sides of the skeleton. In addition, the neural network was trained with mainly gait data, and having the leg straight at 6 o'clock is potentially easier to identify than with a hip and knee angles not observed during walking (at 3 o'clock). Another source of error could be the manual digitisation of joint angles. However, this element has been shown to add a trivial component (i.e. <1.5°) to measurements of joint angles in cyclists (Bini & Hume, 2016) and should be equivalent between methods as both involved manual digitisation 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 pedalled at self-selected sub-maximal intensity and cadence, which limits the assumption that the automated methods will perform similarly during sprints. Clean background was used but it is unclear if the automated method would cope with unclear difference between the cyclists and the background, particularly when videos are collected remotely or outdoors. Moreover, with the use of online video recording methods (e.g. Zoom, Gmeet, etc), webcams with low frame rate (e.g. 30 fps) could result in poor quality video where distortions are observed in body segments. The implications of the use of low-quality video in the accuracy of the automated method should be explored further.

This study used a pre-trained neural network based on a range of images available at a public repository. It is important to note though that these images rarely involve the positions of the body used in this study, which suggest that further training of neural networks may improve the accuracy of artificial intelligence to determine body position on the bicycle. In addition, corrections of joint centres based on the expected movement pattern (i.e. cyclical) should also be implemented to further improve the accuracy of automated methods (Serrancolí et al., 2020).

CONCLUSION: This study demonstrated that an automated method to determine body segments and joint centres using a pre-trained neural network for walking and running gait overestimated torso and knee flexions and underestimated hip flexion and ankle dorsiflexion. However, given changes in angles were not always practically meaningful, implications in terms of bike setup are to be fully detailed. Moreover, it seems unlikely that errors from the automated method will result in large differences in joint forces based on outcomes from prior research.

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