Application of deep learning-based pose estimation methods for clinical gait outcome measures

Logan Wade, Laurie Needham, Murray Evans, Steffi Colyer, Darren Cosker, James Bilzon, Polly McGuigan

Centre for Analysis of Motion, Entertainment Research and Applications, University of Bath, Bath, United Kingdom

email: lw2175@bath.ac.uk

Introduction

- Numerous open-source pose estimation algorithms have been developed, but to date no comparison has been made between algorithms to examine their accuracy compared to marker-based motion capture
- This study aims to compare clinical gait analysis measures (specifically those related to knee osteoarthritis), to examine if gait analysis performed using open-source markerless methods could be employed for clinical gait applications.

Methods

- Fourteen healthy participants performed over-ground constant speed walking while motion capture was obtained from 15 Qualisys cameras and 9 machine-vision cameras at 200 Hz.
- Image data from each machine-vision camera were processed using OpenPose[1] (OP), AlphaPose[2] (AP) and the DeepLabCut[3] (DLC) pre-trained human pose model. Joint centre locations were reconstructed in the 3D space using our previously published fusion algorithm[4]
- Right ankle, knee, hip and shoulder joint-centre locations were used to calculate step length, step width, centre of mass velocity and planar hip and knee joint angles over one stride.
- Outcome measures were compared using Bland-Altman and correlation analysis between marker-based and markerless methods.

Results & Discussion

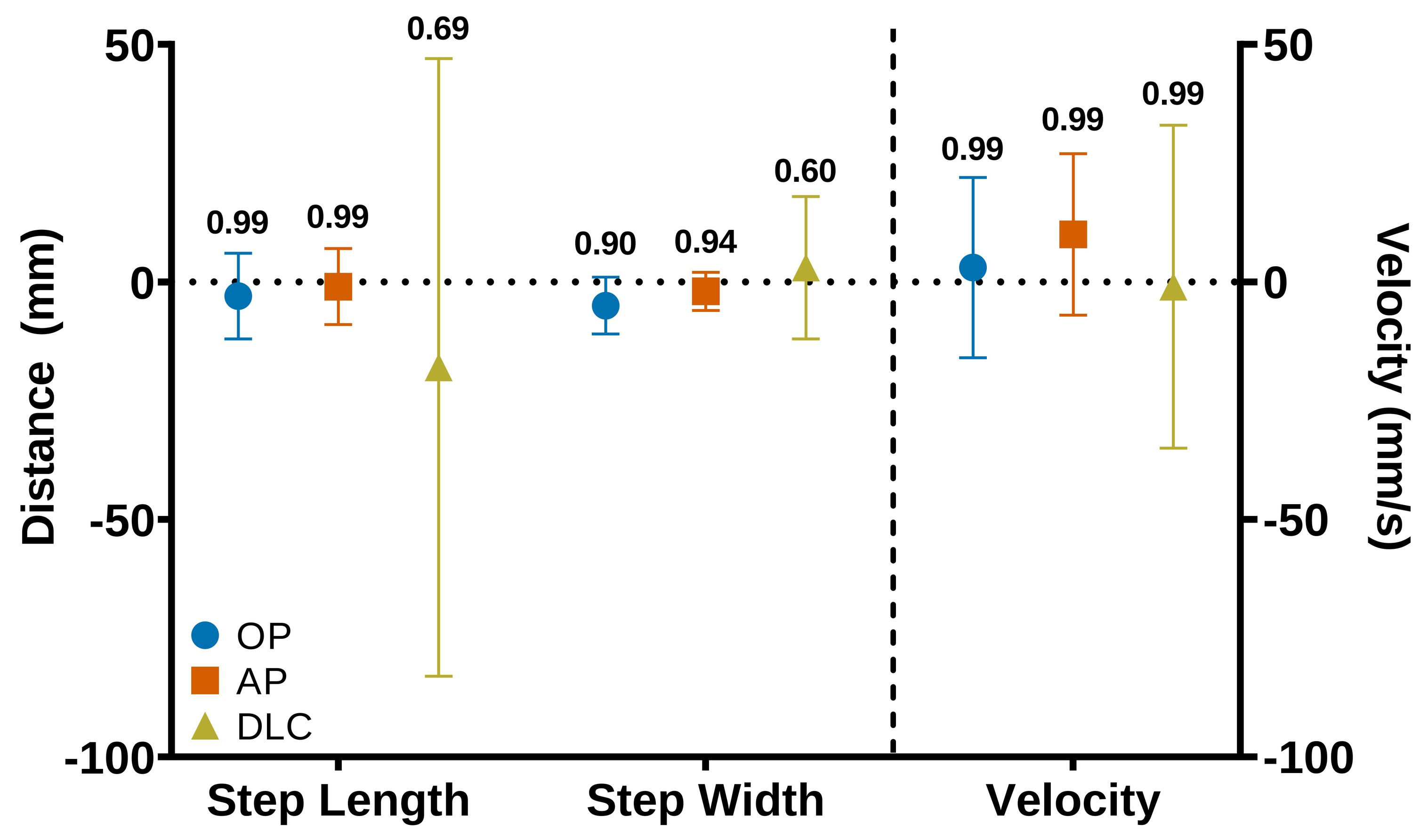
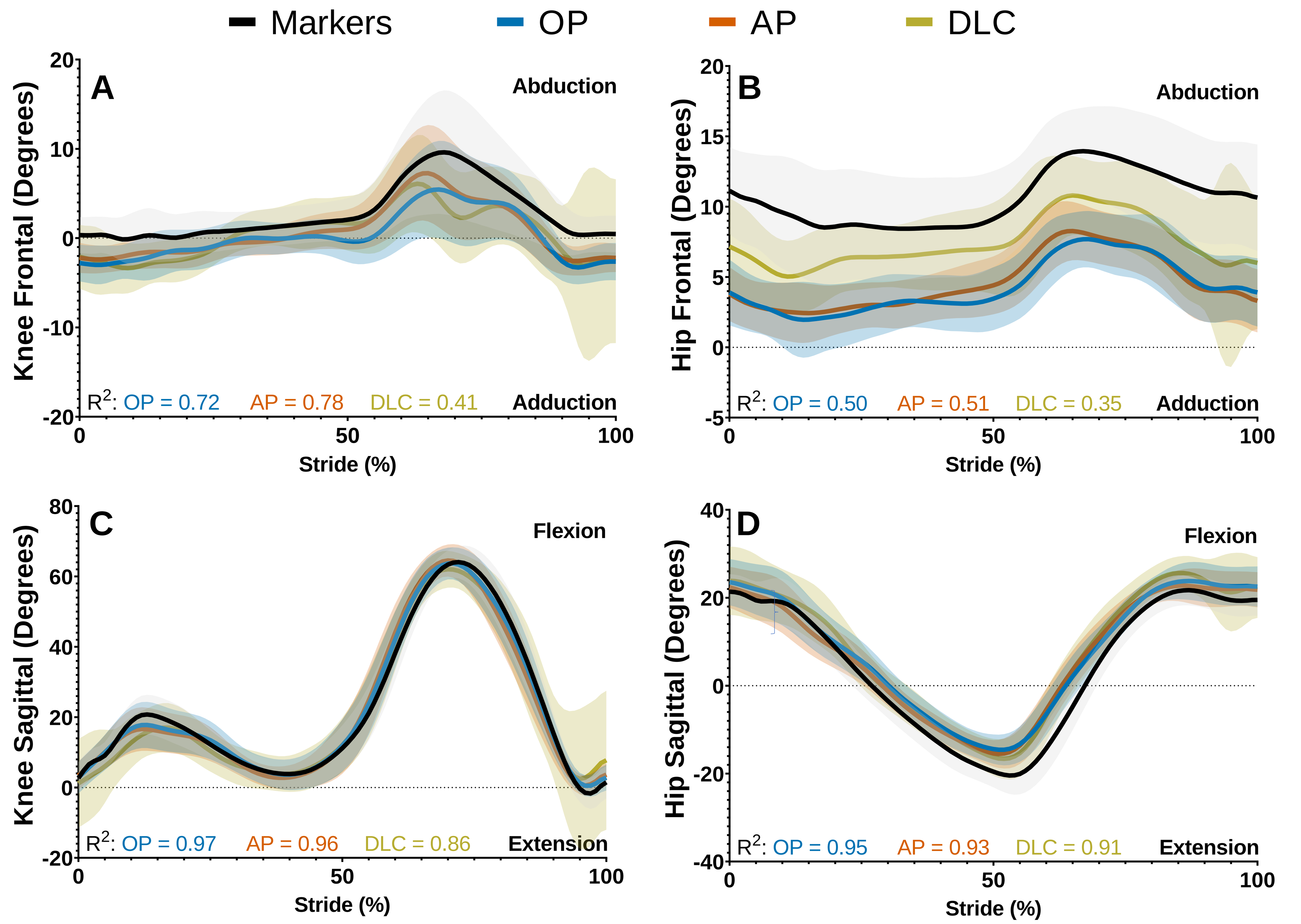


Fig. 1 (Above): Mean (± SD) differences of step length, step width and centre of mass velocity for each of the three markerless methods compared to marker-based motion capture. R^2 values are reported above each variable.

Fig. 2 (Right): Mean (± SD) 2D planar joint angles of the knee (A and C) and hip (B and D) in the frontal (A and B) and sagittal (C and D) plane. Timeseries data is normalised to one stride, beginning at heel-strike. Average R^2 values over one stride are reported for each method.



- AP produced the best agreement to marker- based methods across most variables, followed by OP and DLC.
- Spatial measures obtained from OP and AP had a very small average bias over one stride (Fig. 1), with an R^2 value of 0.99 for step length and velocity, and an R^2 value above 0.90 for step width. Therefore, spatial measures, especially sagittal plane spatial measures, may be sufficiently accurate for clinical applications.
- AP and OP average biases in the sagittal plane were lower compared to the frontal plane (Fig. 2), which was evident in the hip frontal plane that was systematically offset across the whole stride for all methods (Fig. 2B). Systematic offset at the hip was likely due to erroneous manual identification of hip joint centre locations within the training data of the markerless algorithms.
- Planar joint angle variability (SD of bias) was at best, 3.5 ° in the sagittal plane and 2.2 ° in the frontal plane. Average range of motion in the frontal plane for the maker-based method was 10 ° for the knee and 6 ° for the hip. Thus, joint angle errors are likely too large to detect small meaningful changes during gait in many clinical conditions, especially in the frontal plane.

Conclusion

1. **The spatial measures produced by AP and OP may be sufficiently accurate to detect changes in clinical gait.**
2. **Joint angle variability in the sagittal plane and variability and accuracy in the frontal plane are currently too large for most clinical applications.**
3. **Retraining pose estimation algorithms with biomechanically accurate training data may be necessary to obtain accurate joint outcome measures.**
4. **Researchers and clinicians must consider the desired outcome measure and accuracy required for their specific application before implementing these markerless methods in their current form.**

[1] Cao, et al. (2019). IEEE Trans. 43(1), 172-186.
[2] Fang, et al. (2017). In ICCV (pp. 2334-2343).
[3] Mathis, et al. (2018). Nat neurosci, 21(9), 1281-1289.
[4] Needham, et al. (2021). *Sensors*, 21(8), 2889

Acknowledgments: This investigation was funded by CAMERA, the RCUK Centre for the Analysis of Motion, Entertainment Research and Applications, EP/M023281/1