The Performance of Open-Source Pose Estimation Algorithms During Walking, Running and Jumping

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Summary

Several deep learning-based pose estimation methods (OpenPose, AlphaPose and DeepLabCut) were bench-marked against full-body marker-based motion capture. Joint centre locations between systems were evaluated during walking, running and jumping.

Introduction

Biomechanics research traditionally relies on vision-based motion capture tools, either using regular video data and manually annotating points of interest or using maker-based motion capture systems. Deep learning-based pose estimation methods are beginning to provide viable, non-invasive alternatives to traditional motion capture. However, markerless pose estimation methods were not developed specifically for biomechanics applications, thus there is a need to understand their performance in such settings against more established techniques, such as marker-based motion capture. The aim of this study was to evaluate the performance of several open-source pose estimation algorithms against maker-based motion capture during walking, running and jumping.

Methods

Fifteen participants performed walking, running and jumping activities wearing a full-body markerset (44 + clusters). Marker data were captured using a 15 camera Qualisys system (200 Hz) which was synchronised with 9 machine-vision cameras (200 Hz). Image data from each machine-vision camera were processed using OpenPose[1], AlphaPose[2] and DeepLabCut[3]. 2D image plane coordinates from each pose estimation method were back-projected into the 3D space, where the intersect of the back projected rays were taken to represent the 3D joint centre locations. Differences (mean ± SD) in joint centre locations were determined by computing the 3D Euclidean distances between the marker-based (regressed from markers on the segment) and markerless joint centres. Additionally, 95% limits of agreement (LoA) values were computed for the differences in hip, knee and ankle joint centre positions.

Results and Discussion

For all three activities and methods, joint centre locations with the lowest mean differences and SD were observed at the ankle followed by the knee and hip, respectively (e.g., running in Table 1). A large portion of these differences were systematic in nature and likely represent systematic mis-labeling of joint locations in the training data of the markerless pose estimation methods. Additionally, the large random errors that occurred were typically due to false positive detections of joint centres or erroneous switching of contralateral limbs by all pose estimation methods.

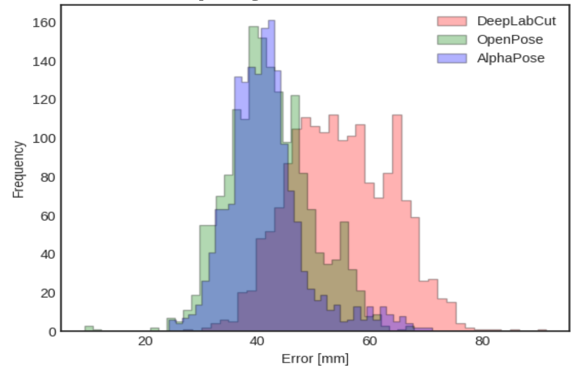

Figure 1: Hip joint location error distributions for each method during all activities.

The lowest mean differences were observed using AlphaPose, followed by OpenPose and then DeepLabCut (Table 1 & Figure 1). These results align with each method's performance on common computer vision benchmarks (COCO, MPII). Further processing of pose estimation results, e.g., outlier detection and inverse kinematics modelling, may be required before acceptable results can be obtained for biomechanics research applications.

Conclusions

OpenPose, AlphaPose and DeepLabCut were benchmarked against marker-based motion capture. Large systematic and random differences were observed for all methods but AlphaPose exhibited the lowest mean errors. Researchers should consider the accuracy and precision requirements of their research applications before implementing these markerless motion capture techniques.

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References

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Table 1: Mean 3D Euclidean differences for lower body joint centres during running.

	Mean Difference (Bias) (mm)			± SD			LoA (Bias + 1.96 SD)		
	OpenPose	AlphaPose	DeepLabCut	OpenPose	AlphaPose	DeepLabCut	OpenPose	AlphaPose	DeepLabCut
Hip	37.95	34.60	45.26	9.41	5.98	9.92	56.39	46.32	64.71
Knee	38.04	41.73	72.45	12.74	21.95	78.04	63.00	84.75	225.41
Ankle	18.50	29.99	89.69	11.09	20.29	154.02	40.25	69.76	391.57