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Uncertainty propagation through triangulation in markerless motion capture

Mathis Renaudin, Antoine Muller,
Thomas Robert, Denis Brizard*

Univ Lyon, Univ Gustave Eiffel, Univ Claude Bernard Lyon 1, LBMC UMR_T 9406, F-69622 Lyon, France

* Corresponding author: denis.brizard@univ-eiffel.fr

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1. Introduction

Markerless motion analysis is promising as it allows to analyze subjects in ecological situation with no subject preparation needed. Its use however, is conditioned by our knowledge of its accuracy, especially in clinical settings where it affects the confidence in diagnosis. Several studies have compared video-based analysis to its marker-based counterpart (Wade et al. 2022) uncovering both systematic and random errors (Needham et al. 2021) and some studies have also investigated the intra- and inter-session repeatability of this method (Kanko et al. 2021). However, in depth sensitivity analysis and uncertainty propagation are yet to be performed.

Markerless motion analysis involves estimating the 2D positions of a set of points of interest (PoI) for each camera using a pose estimation algorithm, and then reconstructing the related 3D points. The accuracy of triangulated 3D points is crucial for the analysis. However, the accuracy of a pose estimation algorithm is difficult to quantify since its results depend on unpredictable factors and vary between algorithms.

The aim of this study is to assess the random errors of two pose estimation algorithms during a simple task and estimate how they propagate through the triangulation process.

2. Methods

2.1 Data collection

Data used in this study were taken from a public dataset (Muller et al. 2025). A single participant (woman,

age: 29 years, height: 157 cm, weight: 60 kg) has been analyzed during a walk. Nine cameras (Miquis Video, Qualisys, Sweden, 60 Hz), distributed around the participant were used to record the movement. The system was calibrated and synchronized using Qualisys Track Manager (QTM - Qualisys AB, Sweden, v2021.1.2).

2.2 Estimation of the pose estimation algorithm random errors

Two pose estimation algorithms have been used to obtain the 2D points: OpenPose (BODY25B model) and RTMPose (COCO133 model). Three PoI were considered: right hip, right knee, and right ankle. Points estimated with a confidence score < 0.3 were excluded.

3D points were triangulated using confidence weighted direct linear transform. These points were then projected in the plane of each camera. The distance between the projected point and the initially estimated point was computed for each point and thereafter named: reprojection error.

Computing the distance of a 2D Gaussian from the origin results in a specific distribution (Rayleigh distribution). This distribution was fitted to the reprojection errors obtained for each of the three PoI and the two pose estimation algorithms. The noise at the output of the pose estimation algorithm was then characterized as a Gaussian distribution with a standard deviation equal to the fitted parameter of the Rayleigh distribution.

2.3 Propagation of the uncertainties through triangulation

For each 2D projected point, ‘noisy’ points were created by adding noise according to the Gaussian distribution previously identified. These ‘noisy’ points were then triangulated and the distance between those and the initially triangulated points was computed and named: propagated uncertainty.

The 95th percentile of propagated uncertainties for each algorithm and each PoI considered was obtained. It is considered to be the 95% confidence interval (95CI) in which a 3D point may be present around the initially triangulated point.

3. Results and discussion

Figure 1 shows the reprojection errors’ distributions and Table 1 provides the standard deviation and 95CI for each PoI for each algorithm.

Disparities in the reprojection errors between PoI and pose estimation algorithms have been evidenced, highlighting the importance of differentiating PoI when propagating uncertainties. Overall, RTMPose displayed lower standard deviations and 95CI than OpenPose for 2 of the 3 considered points.

The propagated uncertainty can be interpreted as the imprecision linked to the uncertainties of the point estimation by the algorithm. If compared to the estimation of markers with optoelectronic cameras, these values (5.96 to 33.5 mm depending on the points) can seem high, but is of the same order of magnitude as the positioning uncertainty of markers to anatomical structures (Della Croce et al. 2005).

The reprojection error distributions here included the nine cameras. Analyzing the distributions per camera would allow us to assess the influence of the viewing angle and would probably improve the Rayleigh fittings and could explain the secondary peak in the Hip PoI. Among the limitations, this study assumed perfect calibration and was limited to the triangulation step. Yet, it provides solid foundation to propagate uncertainties further on the joint angles and torques estimation.

4. Conclusions

This study provided a method to assess the random errors of pose estimation algorithm and propagate those errors through the triangulation process. This highlighted differences between algorithms and PoI in reprojection errors which reverberate on the 3D point’s position uncertainty.

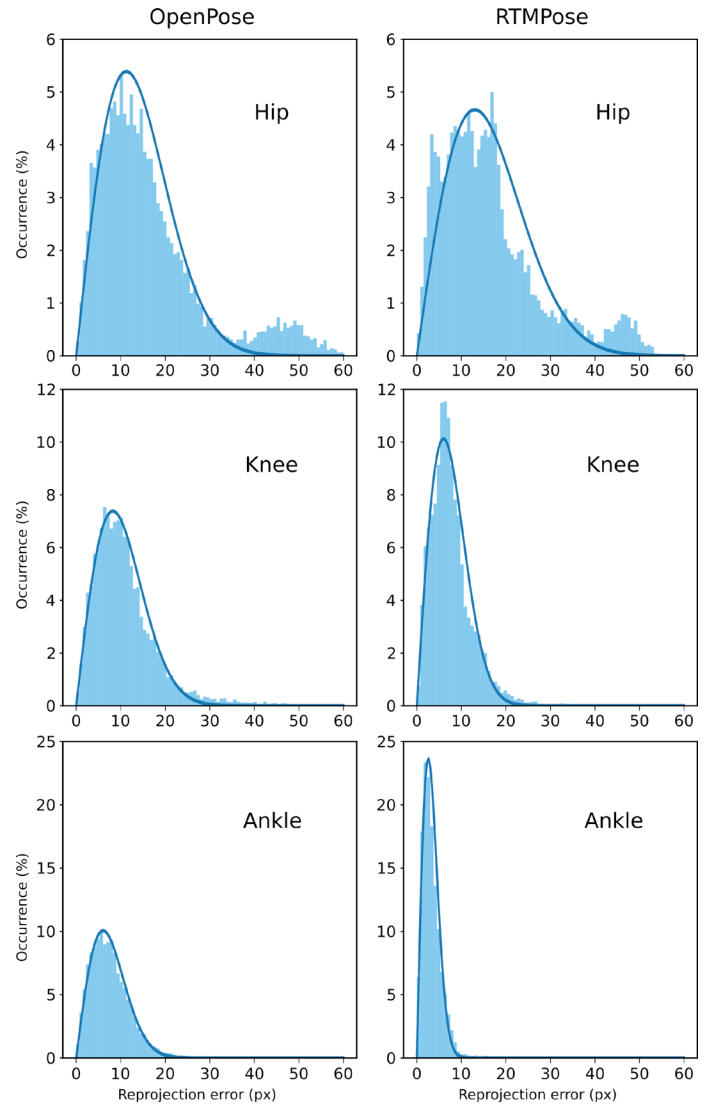


Figure 1. Reprojection errors’ distributions and associated Rayleigh distributions using OpenPose (left column) and RTMPose (right column) for the right hip, right knee, and right ankle (from top to bottom).

Credit: Mathis Renaudin

Table 1. 2D reprojection errors standard deviations (σ) and 95% confidence intervals (95CI) for ‘errored’ 3D points.

Alg.	OpenPose		RTMPose	
	σ (px)	95CI (mm)	σ (px)	95CI (mm)
Param.				
Hip	11.25	26.6	13.0	30.5
Knee	8.21	19.0	5.98	14.0
Ankle	6.03	13.9	2.56	5.96

Credit: Mathis Renaudin

Conflict of Interest Statement

The authors declare no conflict of interest during this study.

Contributor Roles

MR: Methodology, Writing original draft, Software;
AM: Data curation, Methodology, Validation,
Writing- review & editing; TR: Conceptualization,
Methodology, Supervision, Writing- review & editing;
DB: Conceptualization, Funding acquisition,
Methodology, Project administration, Software,
Supervision, Visualization, Writing- review & editing.

Data, software, code availability

Data set used: <https://doi.org/10.57745/LQI2MJ>
(See references).

References

- Kanko, R. M., Laende, E., Selbie, W. S., & Deluzio, K. J. (2021). Inter-session repeatability of markerless motion capture gait kinematics. *Journal of Biomechanics*, 121, 110422. <https://doi.org/10.1016/j.jbiomech.2021.110422>
- Needham, L., Evans, M., Cosker, D. P., Wade, L., McGuigan, P. M., Bilzon, J. L., & Colyer, S. L. (2021). The accuracy of several pose estimation methods for 3D joint centre localisation. *Scientific Reports*, 11(1), 20673. <https://doi.org/10.1038/s41598-021-00212-x>
- Wade, L., Needham, L., McGuigan, P., & Bilzon, J. (2022). Applications and limitations of current markerless motion capture methods for clinical gait biomechanics. *PeerJ*, 10, e12995. <https://doi.org/10.7717/peerj.12995>
- Muller, A., Naaim, A., Dumas, R., & Robert, T. (2025). *Benchmarking dataset for markerless motion capture analysis* (Version 1.0). Recherche Data Gouv. <https://doi.org/10.57745/LQI2MJ>
- Della Croce, U., Leardini, A., Chiari, L., & Cappozzo, A. (2005). Human movement analysis using stereophotogrammetry: Part 4: Assessment of anatomical landmark misplacement and its effects on joint kinematics. *Gait & Posture*, 21(2), 226–237. <https://doi.org/10.1016/j.gaitpost.2004.05.003>