



**HAL**  
open science

## Assessing jump dynamics through a smartphone video

Nicolas Lambricht, Paul Fisette, Christine Detrembleur

► **To cite this version:**

Nicolas Lambricht, Paul Fisette, Christine Detrembleur. Assessing jump dynamics through a smartphone video. 2024. hal-04737932

**HAL Id: hal-04737932**

**<https://hal.science/hal-04737932v1>**

Preprint submitted on 15 Oct 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# Assessing jump dynamics through a smartphone video

Nicolas Lambrecht \*

*UCLouvain-IREC, Woluwe, Belgique*

Paul Fiset

*UCLouvain-MEED, Louvain-la-Neuve, Belgique*

Christine Detrembleur

*UCLouvain-IREC, Woluwe, Belgique*

\*Corresponding author. Email:  
[nicolas.lambrecht@uclouvain.be](mailto:nicolas.lambrecht@uclouvain.be)

**Keywords:** Kinematics; Markerless motion capture; OpenPifPaf; Inverse dynamics; Robotran

## 1. Introduction

The assessment of human motion plays a crucial role in evaluating patients undergoing rehabilitation, particularly those with anterior cruciate ligament (ACL) injuries. The guidelines recommend assessing the symmetry of patient performance in functional tasks like single-leg jumps, while also highlighting the importance of evaluating movement quality during these tasks (Kaplan & Witvrouw, 2019). Parameters that appear pertinent, such as knee flexion angle, maximum vertical ground reaction force (vGRF) during landing (Lepley & Kuenze, 2018), cannot be easily assessed by clinicians in practice. Using deep neural networks for human pose detection and inverse dynamics, smartphone videos offer a promising way not only to assess joint kinematics in functional tasks but also to quantify kinetic parameters.

The objective of this study is to investigate the feasibility of utilizing a simple 2D multibody model to predict external forces based on sagittal plane kinematics extracted from smartphone video footage. The outcomes derived from the smartphone videos were compared with those obtained using a conventional motion capture system.

## 2. Methods

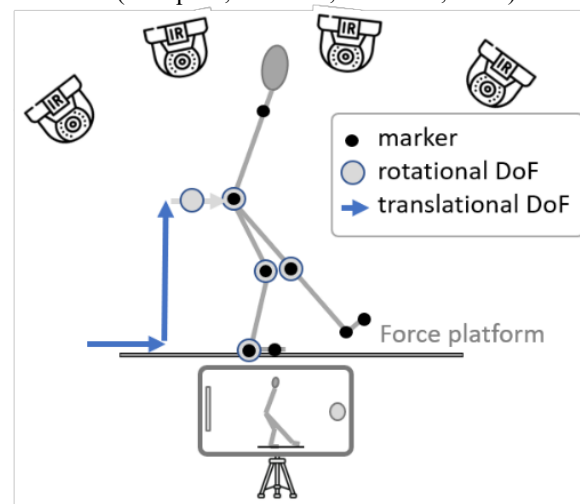
### 2.1 Experimental set-up

Six young healthy men were asked to perform 10 vertical and 10 forward single leg jumps while keeping their arms crossed in front of their chest. Ten reflective markers were placed over anatomical landmarks: on the head of second metatarsal, the lateral malleolus, the lateral epicondyle of the femur, the great trochanter and on the acromion. The motion

was simultaneously captured by a smartphone video and a height-camera's optoelectronic system. The GRF data were collected by a force platform (see Fig.1).

### 2.2 Multibody model

The multibody model of the patient is made of six rigid bodies (see Fig. 1): (1) upper body; contact (2) thigh, (3) shank, and (4) foot; non-contact (5) thigh and (6) shank and foot. The bodies characteristics were extracted from anthropometric table (de Leva, 1996). The "upper body" segment has two prismatic and one revolute actuated degrees of freedom (DoF) with regard to the inertial frame. Each body has one actuated revolute DoF with respect to its parent body, corresponding in the sagittal plane to the flexion movement. Symbolic equations describing the system motion were generated by the multibody software Robotran (Docquier, Poncelet, & Fiset, 2013).



**Figure 1.** Schematic view of the experimental set-up and the multibody model. DoF: Degrees of Freedom  
credit: N. Lambrecht

### 2.3 Data analysis

The video was processed by the OpenPifPaf neural network (Kreiss, Bertoni, & Alahi, 2021). It allowed us to obtain the coordinates of the following keypoints, in pixels: the halluces, the ankles, knees and hips joints and the shoulders. Those coordinates were scaled in meters based on the average experimental thigh segment length and anthropometric expected length. Keypoints and markers trajectories as well as GRFs were filtered using the same low-pass, zero-lag, fourth-order Butterworth filter with a 6Hz cut-off frequency. The kinematics of the multibody system were calculated on the basis of both markers and keypoints coordinates. We used cross-correlation analysis to synchronize the angles from the marker-based and the markerless systems and calculated the root mean square error (RMSE) between the systems.

The symbolic equations generated by the Robotran software were numerically evaluated according to the kinematics inputs of the actuated joints, i.e. the

extracted angles or positions and their associated velocity and acceleration obtained by time derivation. We compared the maximum values of horizontal and vertical component of the GRF normalized by the bodyweight (bw) during landing, as predicted by the model utilizing kinematics from the 2 systems, against the values obtained from the force platform. Agreement was quantified using an Intraclass Correlation Coefficient (ICC 2,1).

### 3. Results and discussion

The comparison of the kinematics derived from the marker-based and markerless systems yields mean RMSE of 4.3°, 3.4° and 3.8° respectively for the ankle, hip and knee joints. The joint kinematics results using OpenPifPaf align with findings from prior studies examining walking, running or squats (Haberkamp, Garcia, & Bazett-Jones, 2022), but using different neural networks.

ICC values are presented in Table 1. The agreement of the model predictions for the maximum horizontal and vertical GRF with the force platform was excellent with marker-based kinematics as inputs. The average mean differences were 0.03±0.06 bw and 0.04±0.04 bw for the vertical and horizontal GRF respectively. With the markerless kinematics, the agreement was good for the vertical GRF and acceptable for the horizontal GRF with average mean differences of 0.02±0.12 bw and 0.07±0.08 bw.

**Table 1.** Intraclass Correlation Coefficients between model predictions and force platform values.

		ICC	Confidence interval	
			Lower	Upper
Marker-based	vGRF	0.91	0.87	0.94
	hGRF	0.90	0.87	0.93
Markerless	vGRF	0.74	0.65	0.81
	hGRF	0.67	0.55	0.76

vGRF, hGRF: maximum landing vertical and horizontal ground reaction forces.

The accuracy of the multibody model's external force predictions is influenced by various factors. These include the simplification of the human body and reliance on anthropometric tables but also the kinematics accuracy. Inaccuracies may arise from palpation errors and soft tissue artefacts when using markers and from the precision of keypoint localization and scaling when employing human pose detection. Working in 2D also exposes the system to potential cross-talk issues.

It would be interesting to extend the study to include more subjects with different characteristics and actual patients.

### 4. Conclusions

The sagittal plane joint kinematics during jumps measured via smartphone video closely align with marker-based assessments. While the predictions of maximum GRFs by the multibody model exhibit excellent agreement with force platform when marker-based kinematics are utilized, they demonstrate less consistency with markerless kinematics. Nevertheless, the ease of use, accessibility, and promising results obtained with this system render it compelling for enhanced ACL patient's assessment in clinical practice.

### Conflict of Interest Statement

The authors have no conflicts of interest to declare.

### References

- de Leva, P. (1996). Adjustments to Zatsiorsky-Seluyanov's segment inertia parameters. *Journal of Biomechanics*, 29(9), 1223–1230. doi: 10.1016/0021-9290(95)00178-6
- Docquier, N., Poncelet, A., & Fiset, P. (2013). ROBOTRAN: A powerful symbolic generator of multibody models. *Mechanical Sciences*, 4(1), 199–219. doi: 10.5194/ms-4-199-2013
- Haberkamp, L. D., Garcia, M. C., & Bazett-Jones, D. M. (2022). Validity of an artificial intelligence, human pose estimation model for measuring single-leg squat kinematics. *Journal of Biomechanics*, 144, 111333. doi: 10.1016/j.jbiomech.2022.111333
- Kaplan, Y., & Witvrouw, E. (2019). When Is It Safe to Return to Sport After ACL Reconstruction? Reviewing the Criteria. *Sports Health: A Multidisciplinary Approach*, 11(4), 301–305. doi: 10.1177/1941738119846502
- Kreiss, S., Bertoni, L., & Alahi, A. (2021). *OpenPifPaf: Composite Fields for Semantic Keypoint Detection and Spatio-Temporal Association* (No. arXiv:2103.02440). arXiv. Retrieved from arXiv website: <http://arxiv.org/abs/2103.02440>
- Lepley, A. S., & Kuenze, C. M. (2018). Hip and Knee Kinematics and Kinetics During Landing Tasks After Anterior Cruciate Ligament Reconstruction: A Systematic Review and Meta-Analysis. *Journal of Athletic Training*, 53(2), 144–159. doi: 10.4085/1062-6050-334-16

**Received date:** 27/03/2024

**Accepted date:** 28/06/2024

**Published date:** XX/XX/2024

Volume: 1

**Publication year:** 2024