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A simple 2D multibody model to better quantify the movement quality of anterior cruciate ligament patients during single leg hop

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Patients with anterior cruciate ligament reconstruction frequently present asymmetries in the sagittal plane dynamics when performing single leg jumps but their assessment is inaccessible to health-care professionals as it requires a complex and expensive system. With the development of deep learning methods for human pose detection, kinematics can be quantified based on a video and this study aimed to investigate whether a relatively simple 2D multibody model could predict relevant dynamic biomarkers based on the kinematics using inverse dynamics.

Six participants performed ten vertical and forward single leg hops while the kinematics and the ground reaction force "GRF" were captured using an optoelectronic system coupled with a force platform. The participants are modelled by a seven rigid bodies system and the sagittal plane kinematics was used as model input. Model outputs were compared to values measured by the force platform using intraclass correlation coefficients for seven outcomes: the peak vertical and antero-posterior GRFs and the impulses during the propulsion and landing phases and the loading ratio.

The model reliability is either good or excellent for all outcomes (0,845 ≤ ICC ≤ 0.987).

The study results are promising for deploying the developed model following a kinematics analysis based on a video. This could enable clinicians to assess their patients' jumps more effectively using video recordings made with widely available smartphones, even outside the laboratory.

Keywords: Movement quality, Anterior cruciate ligament, Ecological assessment, Ground reaction force, Multibody model, inverse dynamics.

INTRODUCTION

The anterior cruciate ligament "ACL" rupture is a common injury in young and active individuals with an estimated annual incidence of 68.6 per 100,000 person-years[1]. The golden standard treatment is a reconstructive surgery with an autologous graft[2] followed by a criterion-based rehabilitation. ACL injuries often lead to long-term adverse health issues such as early osteoarthritis[3] and to increased health economic costs[4]. Despite extensive research dedicated to predicting and preventing both primary ACL injury and reinjury, the annual incidence seems to increase over recent decades[5] and patients still exhibit a greater risk of sustaining a second ACL injury[6] and a higher risk for injuring other knee structures such as menisci, cartilage and other ligaments[7]. Current good practice guidelines for return to sport testing rely on psychological and strength assessment as well as a cluster of functional tests typically involving single leg hops[8]. Hops clusters have been widely adopted by clinicians as they are easy to administer and to interpret. The limb symmetry index (LSI), defined as the ratio between the performance reached with the injured and the uninjured side, is usually used to quantify the recovery. Nevertheless, this approach is currently criticized as patients with symmetrical performance can still exhibit compensatory strategies that are only detectable when assessing movement quality[9]. Some strategies are also believed to contribute to the risk for second ACL injuries[10] and early osteoarthritis[11].

When looking at the deficits present in ACL patients during jumping, the sagittal plane dynamics seem particularly affected. The activation patterns in lower-body muscles is modified[12] and the peak knee flexion angle, the knee flexion range of motion, the peak knee extension net torque and the vertical GRF (vGRF) are considered as the most important biomarkers[13,14]. The golden standard method to measure such parameters is by using an optoelectronic system in conjunction with force platforms. However, these devices are barely used in non-research settings because they are expensive, they require a dedicated space and skilled operators and they lack of portability[15]. There is a need for a user-friendly tool that allows health care professionals to measure the quality of movement in ACL patients while performing single leg hops. Different methods have been developed to help clinicians measure dynamic parameters in their practice or even on-the-field during various daily life activities such as walking[16], running[17] and jumping[18]. The kinematics (2D or 3D) is usually computed using data from inertial measurement units or video captures. Different devices and methods have been developed to measure dynamic parameters. For instance, the vGRF can be directly quantified with either portable force platforms[19] or pressure-sensing insoles[20] but can also be computed by inverse dynamics using kinematics data[21] or be estimated by machine learning methods[15].

Smartphones are widely used in the general population and can serve as measurement devices inside the clinical practice[22]. With the significant advances in the field of computer vision, very high performance are already achieved by 2D single-person pose estimation methods using deep learning techniques on monocular image[23]. The sagittal plane kinematics could be quantified accurately based on a smartphone video during different tasks such as gait[24] and single leg squat[25]. Nevertheless, the quantification of the dynamic parameters from a 2D video is more challenging. The use of inverse dynamics based on kinematic data is an interesting approach. This method not only enables the calculation of external forces applied to the subject but also facilitates the derivation of values for internal net torques.

The primary goal of this study is to establish a simple 2D multibody model that can predict the external forces acting on a subject during single leg hops based on the body kinematics in the sagittal plane that one may expect to obtain from a smartphone video using inverse dynamics. The movement kinematics was measured by an optoelectronic system mimicking results from a smartphone video. A secondary objective involves exploring potential impacts of lower sampling rates on the accuracy of the model predictions. This investigation is motivated by two primary reasons. Firstly, smartphones manufacturers have generally settled on having 30 or 60 frames per second which is inferior to the optoelectronic system 100Hz acquisition frequency and this may impact the metrics of landing dynamics[26]. Secondly, human pose detection programs process images sequentially, meaning the processing speed of a video is inversely proportional to the acquisition frequency.

METHODS

Participants

The participants were 6 young healthy men (mean (SD) age: 23.5 (4.2) years old, height: 1.8 (0.1) m, body mass: 70.4 (4.9) kg) who had not suffered any lower extremity musculoskeletal injuries for at least 6 months.

This study was approved by the ethics committee of our university. The purpose of the study was explained to the participants and they all provided their written informed consent to the use of their anonymized data before the experiments.

Procedure

The participants wore only a dark boxer short and were barefoot to eliminate possible shoes effects during the experiment. Eighteen reflective markers were placed over anatomical landmarks, sixteen on the pelvis and the lower limbs according to the Vicon “Plug-in Gait lower body” model setup and one on the middle of the lateral edge of each acromion (Fig. 1A).

The body kinematics was motion-captured at a rate of 100Hz using a height-camera optoelectronic system (Vicon V5 Motion Systems, Oxford Metrics Ltd., Oxford, UK) and the GRF data were collected by a time synchronized force platform at 1000Hz (Gaitway® 3D, Arsalis, Glabais, Belgium). Markers trajectories and GRFs were filtered using a low-pass, zero-lag, fourth-order Butterworth filter with the same cut-off frequency before being used by the Plug-in Gait lower body model and being exported. The outcomes of inverse dynamics are subject to the influence of the cut-off frequency applied in processing kinematic data. Given the absence of a standardized cut-off frequency among various research teams investigating jump dynamics in ACL patients, our study focuses on examining three commonly employed frequencies: 6Hz, 10Hz and 15Hz.

The tasks were single leg forward hop and single leg vertical hops, as recommended when assessing ACL patient[27]. Participants were asked to stand still on one foot, to jump either forward or upward depending on the task and to land on the same lower limb and stabilize as quickly as possible in a single leg standing for at least 2 seconds. They were requested to perform the movements in a direction such that the Y-Z plane of the lab coordinate system corresponds to the subject sagittal plane. They also had to keep their arms crossed in front of their chest with the middle fingertip of each hand on the anterior edge of the contralateral acromion during the whole task. If participants did not respect one of the above requirements, the trial was discarded. Five successful trials for both tasks with each lower limb were recorded.

Multibody model

The participants' model is composed of a seven rigid bodies system as showed in Fig.1 B. The bodies can move in the inertial frame and relative to each other by actuation of either prismatic or revolute joints allowing translational and rotational degree of freedom, "DoF", respectively. The segment "pelvis + low-back" has 2 prismatic and 1 revolute DoF with regard to the inertial frame. Each body has one revolute DoF with respect to its parent body, corresponding in the sagittal plane to the flexion/extension movement. Experimental values for the pelvis tilt, the hips, knees and ankle joint angles were extracted from the Vicon Plug-in Gait Lower body model results. The spatial localization of the pelvis center of mass was assumed to be located at the center of the four superior iliac spines. The upper body flexion/extension angle was computed using the joint coordinate system approach[28] knowing the spatial position of the two shoulders and the pelvis, and assuming a pure sagittal 2-D movement. The bodies characteristics were extracted from anthropometric table[29]. Symbolic equations describing the system motion were generated by Robotran, a software environment for simulating and analyzing multibody systems developed at the Université catholique de Louvain in Belgium[30,31].

Data analysis and outcomes

Spyder scientific environment (Python 3.10) was used for the data processing. The inverse dynamics aimed to compute the joints actuation force and torque required by the jump motion. The symbolic equation 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. The ground reaction forces have been obtained by two different methods yielding the same results. They both assume that the only external forces acting on the rigid body system except gravity is the GRF. The first one computes the GRF components in the sagittal plane as the inverse dynamic solutions for the two translational actuated joints associated with the pelvis motion (see Fig. 1 B). The second method uses Newton's law and considers that these reaction forces are the algebraic summation of the mass-acceleration products of the 7 rigid bodies. Equations

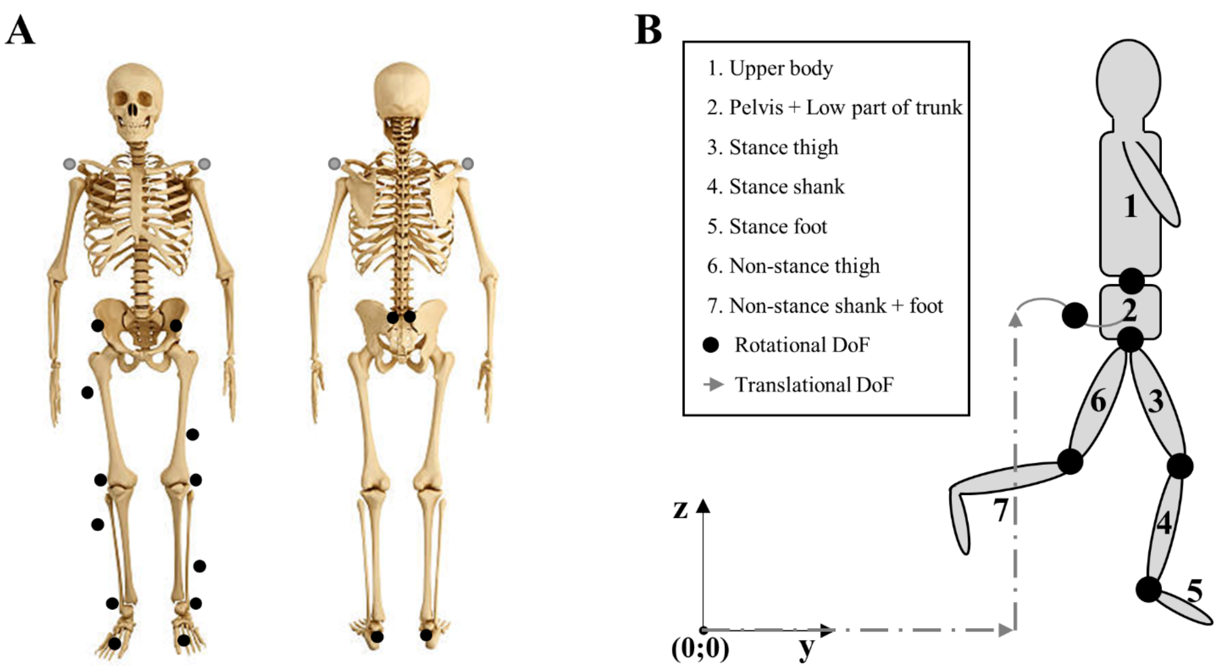

Fig. 1 — A. Position of the markers on the participants. The 16 markers (black circles) on the pelvis and the lower limbs are for the Plug-in Gait lower body model. The two additional markers (grey circles) are localized on the edge of each acromion. B. Graphical representation of the multibody model composed of seven rigid bodies. Black circles represent revolute degrees of freedom "DoF" and arrows stand for translational DoFs.

to compute the GRF in the antero-posterior (F_y) and vertical (F_z) directions are respectivel[32] :

$$F_y = \sum_{i=1}^{7} m_i a_{yi}$$

$$F_z = \sum_{i=1}^{7} m_i (a_{zi} + g)$$

where m_i is the mass of the i^{th} segment, a_{yi} and a_{zi} are the accelerations of the i^{th} segment center of mass in the y and z directions and g is the acceleration due to gravity (9.81m/s²).

Hops were split into three distinct phases: the propulsion phase was defined as 400 ms prior to take off until take off, the landing phase from initial contact to peak knee flexion 27 and the flight phase in between where the GRF has to be zero as there is no actual contact with the ground. Take off and initial contact were considered as the points when the vertical GRF became less and more than 5% of the participant's body weight respectively.

Different outcomes useful for healthcare professionals or biomarkers, presented in Fig. 2, were extracted from both the multibody simulation results and the force platform measures for comparison. They were all normalized by the participant's body weight. The peak ground reaction forces were the highest value in the vertical, "vGRF", and antero-posterior, "apGRF", directions during the propulsion and the landing phases. The propulsion and landing impulses were calculated as the integral of the vGRF curve with respect to time over each phase. The loading rate, "LR", was calculated as the peak landing vGRF divided by the time it took to reach it[26].

The secondary aim of this study was to investigate the possible effect of lower sampling rates on the accuracy of the model predictions. The markers trajectories were artificially down-sampled from 100Hz to 30Hz with a 10Hz step using a linear interpolation of the discrete experimental points prior to a low-pass, zero-lag, fourth-order Butterworth filter with a 10Hz cut-off frequency. The percentage of deviation from the results obtained with the actual sampling frequency of the optoelectronic system, i.e. 100Hz, was computed for the seven outcomes, for each trial and for each sampling frequency "v" using the following equation:

$$PDF100_{outcome,v} = 100\,\frac{(value_{outcome,v} - value_{outcome,100})}{value_{outcome,100}}$$

where $value_{outcome,v}$ is the model result for the outcome when the model kinematic input was down-sampled to v Hz and$value_{outcome,100}$ is the model result for the outcome when the model kinematic input was not down-sampled (100Hz). 2.5. Statistics

The reliability of the model for the prediction of the above-mentioned outcomes was assessed using a two-way random Intraclass correlation coefficient (ICC 2,1). A score of 1 represents perfect reliability with no measurement error, values of ICC > 0.9 were considered as excellent, 0.70-0.89 as good, 0.40-0.69 as acceptable and <0.4 as low (Shrout and Fleiss, 1979).

RESULTS

Fig. 3 shows the model predicted values versus the actual ones measured by the force platform for the different outcomes. During the propulsion phase of single leg vertical and horizontal hops, the multibody model prediction for the vertical and anteroposterior ground reaction forces and the impulse showed excellent agreement with the force platform values with ICC above 0.96, 0.91 and 0.96 respectively (see Table I). The three filter cut-off frequencies yielded similar results for the outcomes in terms of absolute values and ICC.

During the landing phase, the reliability of the model to predict the vGRF, the apGRF, the impulse and the LR depends on the filter cut-off frequency used on both kinematics input data and force platform measures. It was excellent (> 0.91) for all the outcomes with 6Hz, for all the outcomes but the LR (ICC = 0.89, good) with 10Hz and for all the outcomes but the LR (ICC = 0.845, good) and the vGRF (ICC = 0.873, good) with 15Hz.

The effect of a decreased sampling rate on the model prediction is showed in Fig. 4 where the percentages of difference with the values obtained at 100Hz for every outcome across trials are plotted as a function of the decreased frequency. For all the outcomes, the PDF100 are low with average values ranging between -2% and 1%.

DISCUSSION

Multibody model

We established a simple 2D multibody model that could predict the vertical and anteroposterior ground reaction forces acting on subjects all along single leg vertical and horizontal hops on the basis of the sagittal plane body kinematics. During the propulsion phase, the reliability of the model to predict the different outcomes was excellent and barely affected by the

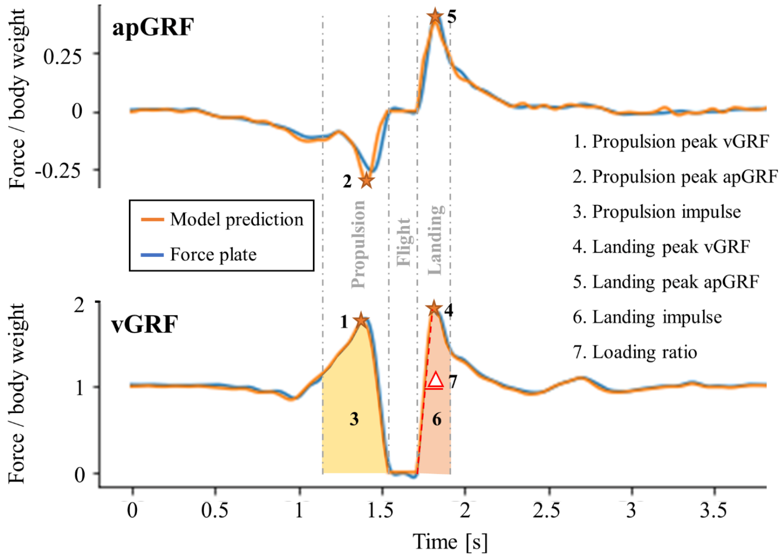

Fig. 2 — Example of model predicted (orange line) and force platform measured (blue line) antero-posterior and vertical normalized ground reaction forces during a single hop with a 10Hz cut-off frequency. The different outcomes of this study are represented on the curves.

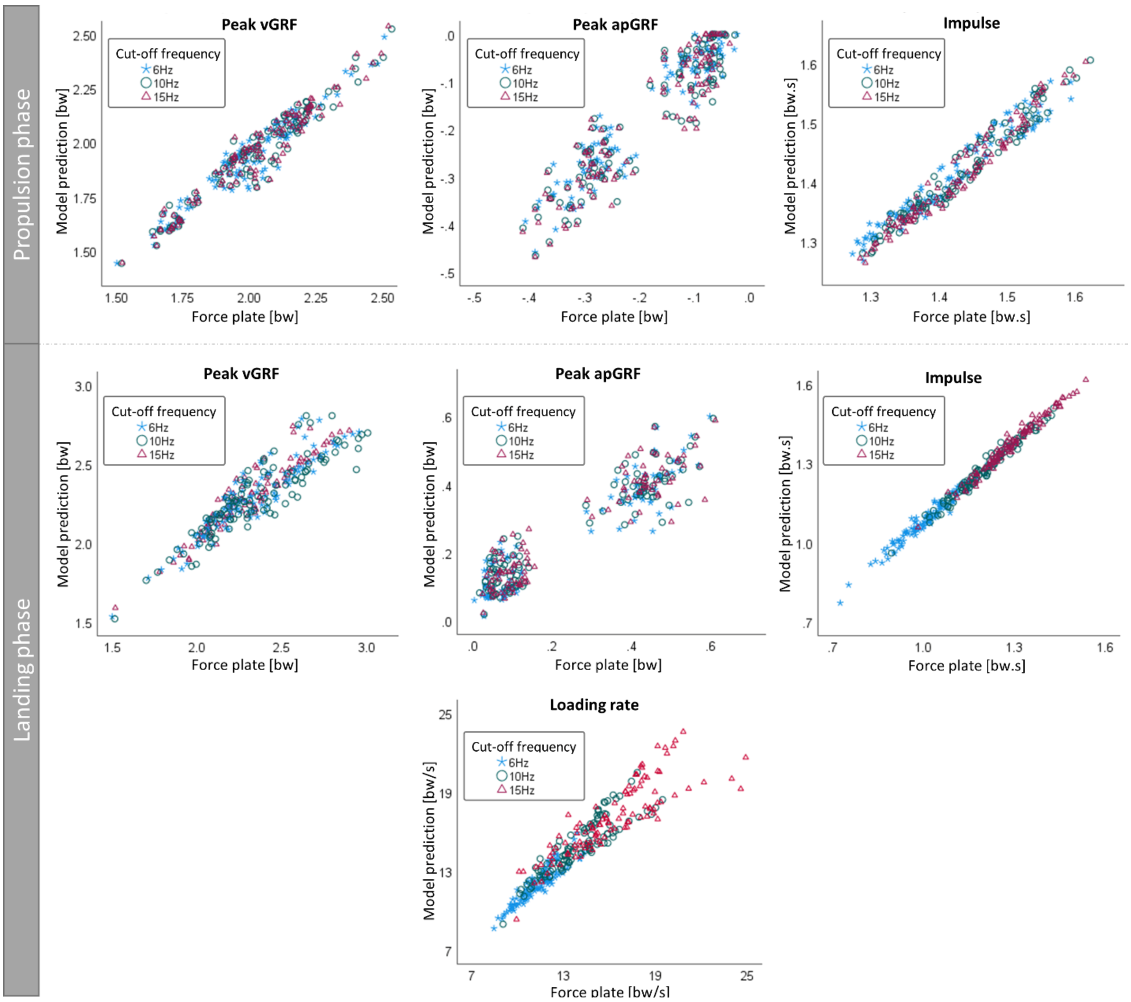

Fig. 3 — Scatter plots of the model predicted values versus the force platform measurements for the seven outcomes. Results obtained using filter with the three different cut-off frequencies (6,10 and 15Hz) on the kinematic and force platform raw data are presented. All outcomes have been normalized by the participants bodyweights, "bw".

Table I. — Intraclass correlation coefficients and associated 95% confidence intervals for the seven outcomes and for the three filter cut-off frequencies.

		Propulsion phase			Landing phase		
Cut-off frequency		ICC	95% confidence interval		ICC	95% confidence interval	
			Lower bound	Upper bound		Lower bound	Upper bound
Peak vGRF	6 Hz	0.966	0.950	0.976	0.930	0.900	0.952
	10 Hz	0.966	0.951	0.977	0.910	0.871	0.938
	15 Hz	0.965	0.949	0.976	0.873	0.819	0.911
Peak apGRF	6 Hz	0.941	0.915	0.960	0.919	0.884	0.945
	10 Hz	0.917	0.881	0.943	0.913	0.874	0.940
	15 Hz	0.910	0.872	0.938	0.911	0.871	0.938
Im-pulse	6 Hz	0.967	0.952	0.977	0.982	0.974	0.988
	10 Hz	0.976	0.966	0.984	0.986	0.980	0.991
	15 Hz	0.980	0.970	0.986	0.987	0.981	0.991
Loading rate	6 Hz	/	/	/	0.917	0.881	0.943
	10 Hz	/	/	/	0.890	0.843	0.924
	15 Hz	/	/	/	0.845	0.780	0.892

cut-off frequency used for both model kinematics inputs and force platform measurements. However, during the landing phase, the model reliability varied with the chosen cut-off frequency. These results can be understood by looking at the time curves of both raw and filtered measured GRF (Fig.5A) and model predicted GRF (Fig. 5B) during a hop.

The measured and predicted GRF variation during the propulsion phase was sufficiently slow that values were similar whatever the cut-off frequency used and fitted the raw measured GRF. On the contrary, a high frequency impact peak GRF occurs during the landing phase. This impact peak is usually studied using methods ranged from no filter to a low-pass filter with a 25Hz cut-off frequency[34] and is flattened with decreased cut-off frequencies (see Fig.5A). The influence of ground impact on the measured and model predicted peak vGRF increased together with the cut-off frequency of the filter applied on both the raw force platform and the kinematic data. This led to increased discrepancy between measured and predicted peak vGRF values. As a consequence, the model agreement was excellent for all outcomes with 6Hz but, for higher cut-off frequency, it was only good for the most sensitive outcomes and remained excellent for the others. The LR is known as being highly dependent on the filtering method and the cut-off frequency[35] as it depends on both the value of the vGRF and the time to reach it. The landing peak apGRF and vGRF are directly linked to the ground impact. The impulse is the integral of the vGRF over the landing phase and was less affected by the peak vGRF value. These findings concerning the outcomes sensitivity were consistent with previous work[26].

In the context of ACL patients' assessment, the knee internal net torque seemed to be a relevant biomarker[13,14] and could potentially be estimated with the present model. It is usually computed by inverse dynamics using a multibody system, the bodies kinematics and measurement from a force platform. The force and movement data have to be filtered with the same filter so that the torque is not affected by artefacts due to inconsistencies in the equations of motion[36]. It has also been showed that the GRF curve modification due to low cut-off frequency was detrimental for intersegmental forces but, in contrast, led to more accurate net joint torques during inverse dynamics calculations[37]. Therefore, although the impact peaks present in the raw measured GRF could not be predicted by the model, predictions were still very interesting as they showed a good agreement with the filtered measured GRF. Consequently, the joint net torque could be computed by inverse dynamics using the developed multibody system, the body kinematics and applying the predicted GRF on the contact foot. Nevertheless, since the exact location of the center of pressure over time is not known, it would be only possible to calculate an estimate of the lower limb internal net joint torques. This estimate might already give a valuable information to the clinicians.

Sampling frequency

The secondary part of the present study determined the impact of sampling frequency on the model GRF

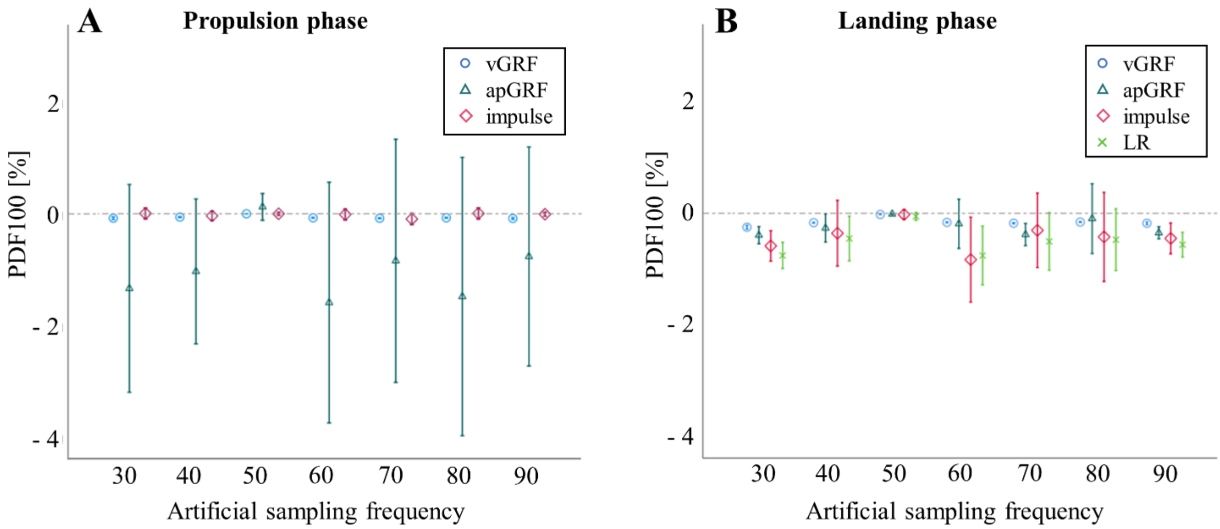

Fig. 4 — Distributions of the percentage of difference between the values obtained at artificially decreased frequencies and the values obtained at 100Hz (PDF100) for the seven outcomes. The markers point the mean values and bars represent the 95% confidence intervals.

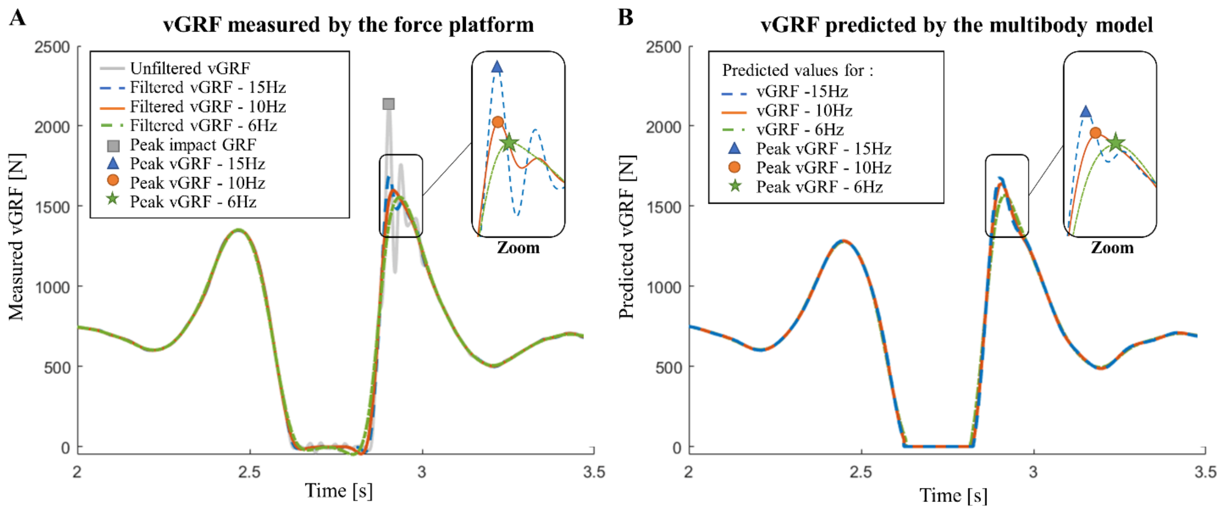

Fig. 5 — Typical temporal evolution of vGRF (A) measured by the force platform and (B) predicted by the multibody model during a forward single leg hop. The grey solid line in A corresponds to the raw data. The dashed blue, the solid orange and the dash dotted green lines stand for the filtered measured vGRF with cut-off frequencies of 15Hz, 10Hz and 6 Hz respectively. The measured and predicted landing peaks vGRF for the three cut-off frequencies are highlighted in the zoom.

prediction. For all the outcomes, the PDF100 (see Fig. 4) are low with average values ranging between -2% and 1%. The kinematic data filtering might explain the similarity of the results with decreasing sampling frequencies as higher frequency variations were dumped by the filter and only the low frequencies signals, unaffected by the down-sampling were used as inputs for the model. This result was interesting as, even though some smartphones could reach 120Hz or even 240Hz, most of the current ones can record high definition videos at 30 and 60Hz. In addition, a lower acquisition frequency means a reduced number of images to process and, therefore, a decreased tracking time.

Limitations

One of the limitations of this study is that the model was limited to the two-dimensional sagittal plane. There are two main reasons for that: on the one hand, sagittal plane dynamics seems to be particularly important while assessing ACL patients[13,14]. On the other hand, deep learning-based methods[38,39] have achieved very high performances in 2D single-person pose estimation from a single source video but the 3D is more challenging especially due to the lack of large-scale datasets annotated with 3D human poses [23]. The developed multibody model could be upgraded to 3D when the kinematics provided by 3D human pose estimation has reached a higher accuracy.

It should be noticed that the model has only been tested on Caucasian males with anthropometric data corresponding to this specific population. It would be interesting to test the model on other populations, using appropriate anthropometric data for the seven rigid bodies.

Another limitation is that down-sampled measurements from an optoelectronic system were used to mimic those from a smartphone video. Nevertheless, the transition from one to the other is not straightforward and different sources of imprecision could affect the model results. Firstly, joint center locations obtained through markerless systems still lack consistent consistently comparability with those derived from optoelectronic system. Secondly, the tracking accuracy of the keypoints on a video cannot compete with that of the optoelectronic system and this will introduce additional noise to the kinematics data. Finally, other potential artefacts related to the lower frequency acquisition and inferior camera performances such as the image quality and the motion blur were not considered in this study. Indeed, with lower acquisition frequencies, the fastest moving bodies will show motion blur bringing an additional source of imprecision for the keypoints localization.

CONCLUSION

This study aimed to establish a patient 2D multi-body model that could predict GRFs during single leg hops from body kinematics in the sagittal plane. Our model was tested with kinematic inputs filtered with three different cut-off frequencies generally used in previous studies looking at the jump dynamics of ACL. The reliability of the model, i.e. the agreement between the predicted values and the filtered values from the force platform, was either good or excellent depending on the cut-off frequency and the outcome sensitivity to filtering. The sensitivity analysis of the model with respect to the acquisition frequency showed that the results were not affected by a down-sampling as low as 30Hz. The results of this study are encouraging for the use of smartphone video to provide the clinicians with values for the GRF and estimates for the ankle, knee and hip joint kinetics during single leg tasks in addition to relevant kinematic data. Further work based on the developed 2D multibody model using kinematics from actual smartphone videos is needed to allow health care professionals to use it in their clinical practices.

Conflict of interest statement: The authors declare that they do not have a conflict of interest.

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