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Foot contact detection through pressure insoles for the estimation of external forces and moments: application to running and walking

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1. Introduction

In motion analysis studies, classical inverse dynamics methods require knowledge of the ground reaction forces and moments (GRF&M) to compute internal forces. Force platforms are considered as the gold standard to measure GRF&M applied to the feet. Such devices reduce the ecological aspect of the experimental conditions by limiting the analysis area. Estimating external forces from motion data and dynamic equations circumvents this limitation at the expense of accuracy.

In such an estimation method, the inverse dynamics problem is undetermined since contact is modelled by multiple points representing the potential ground-foot contact area. The contact is systematically multiple during double support phases and using multi-point models that Dorn T. W. et al. (2010) recommends. An optimization approach distributes the forces preserving the global equilibrium on the active contact points according to physiological assumptions, e.g. minimizing external forces. A contact point is considered active when that point on the foot is in contact with the ground. Contact detection is usually based on kinematic parameters such as height and velocity thresholds. Fritz et al. (2019) showed that the tuning of those parameters according to the subject and the task affects the accuracy of the method. Obtaining the correct setting remains time-consuming and requires biomechanical knowledge to be effective.

This abstract presents a study that evaluates the potential of pressure insoles to detect contact in an external force estimation method. Two contact detection methods are evaluated: one is based on kinematic thresholds and the other is based on pressure insole data. The evaluation method consists of comparing the GRF&M estimated by both methods with those measured by the force platforms during running and walking.

2. Methods

Experimental data consisted of 59 running and 58 walking trials performed by 14 subjects (29±2 years old, 1.80±0.1m, 70±10kg). Motion capture data (46 markers placed on standardized anatomical landmarks according to ISB recommendations made in Wu et al. (2002) and Wu et al. (2005)) were recorded with an optoelectronic motion capture system from Qualisys (200Hz). External forces data were recorded with two AMTI force platforms (2000Hz). Underfoot pressure was recorded by Moticon pressure insoles (100Hz, 16 pressure cells per insole, Figure 1). These wireless insoles were inserted inside the subjects' shoes.

The biomechanical model was composed of 17 rigid segments linked by 16 joints corresponding to 39 degrees of freedom. The geometric parameters were calibrated to each subject from motion data. The inertial parameters were retrieved from anthropometric tables. Joint coordinates were computed using multibody kinematic optimization. Based on the method reported in Fluit et al. (2014), the GRF&M were estimated using an optimization approach considering a set of 16 discrete contact points per foot at the centre of each pressure cell (Figure 1). At each frame, a Sequential Quadratic Programming method estimated the external forces distribution on each active contact point by minimizing the quadratic sum of external forces while respecting the whole-body dynamics equilibrium.

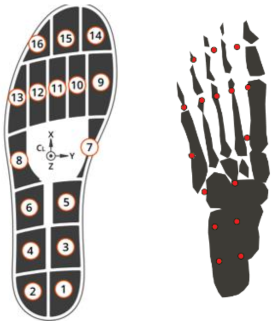

Figure 1 Pressure sensors and contact points repartition

Two contact detection methods were used to determine the active contact points considered for estimating the GRF&M at each frame.

The first contact detection method used **kinematic thresholds** (**KT**). A contact induces a zero-relative velocity between the foot and the ground, which implies a constant and determinable distance. In this case, a contact point is considered active if its vertical position is less than $\boldsymbol{z_{crit} = 0.05m}$ and its velocity norm is less than $\boldsymbol{v_{crit} = 0.8m/s}$ (similar to empirical values in Fluit et al. (2014)).

The second contact detection method exploited **insoles informed** (**II**) contact detection. A contact point was considered active with a pressure higher than $\boldsymbol{1.5N/cm^2}$ on the closest pressure cell. Pressure data were filtered: low intensity peaks were removed (empirically defined as $<$

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$\mathbf{2N/cm^2}$ and $\mathbf{< 0.03s}$ for a $\mathbf{0.25N/cm^2}$ pressure accuracy).

Both methods were implemented and run with the CusToM Matlab toolbox (Muller et al., 2019). The estimated GRF&M using KT and II were evaluated by comparing them to the measured values. The RMSE were normalized by subject body mass and statistically compared with Friedman tests, considering the GRF&M components as independent. The confidence level was set to $\boldsymbol{p = 0.05}$.

3. Results and discussion

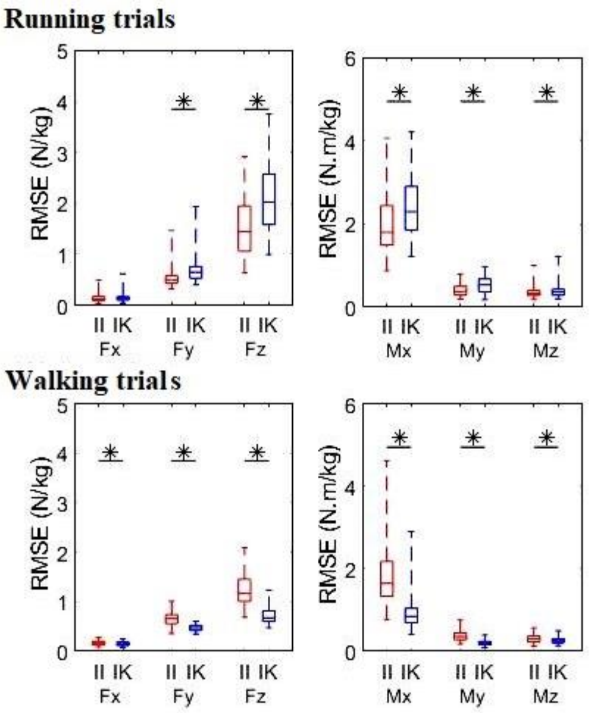

Figure 2 RMSE of the estimated GRF&M for the running trials and walking trials with II (red) and IK (blue) detection method

The RMSE were comparable to the RMSE from Fluit et al. (2014). The vertical component of RMSE during running was higher due to the dynamism of the task. The II method significantly decreased the efficiency of GRF&M estimation for walking motion as shown in Figure 2. It improved the efficiency of GRF&M estimation for running trials as shown in Figure 2.

KT and II methods were performed with arbitrary thresholds, chosen for their fair performance in preliminary studies. KT thresholds can be adapted to the subject movement to improve the current results, especially for running trials. II pressure thresholds may as well be adapted to enhance contact detection in motions with low dynamics such as gait. These thresholds can be adapted by machine learning techniques using kinematic quantities and observed contacts.

The biomechanical model consists of a single solid to model the foot. This simplification affects the kinematic estimation of the foot and the accuracy of KT method. A model with two solids for the foot should be considered.

Pressure data were recorded at a lower acquisition frequency than motion data and required resampling of the pressure data, limiting its performance by generating false positive active points at some frames.

To better understand the performance of both methods, especially during toe off and heel strike, a statistical parametric mapping comparison between estimated and measured forces might be relevant.

Insoles may also be useful for estimating the centers of pressure. Such information may improve force distribution by adding a constraint on their position in the algorithm.

4. Conclusion

Pressure insoles have shown real potential for detecting contact and they represent a new data source about force distribution. In this study, they improved the GRF&M estimation for running trials. Although pressures insoles may hinder the subjects, being inserted into their shoes, they can potentially be used in uneven or inclined floor situations, unlike threshold-based contact handling. Such approaches may be of interest to enlarge the in-situ motion analysis perspectives.

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