Ground Reaction Forces and Moments Estimation from Embedded Insoles using Machine Learning Regression Models

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***Abstract*— The objective of this paper was to assess the possibility of estimating 6D ground reaction forces and moments during continuous double supports exercises using instrumented force insoles. Thanks to machine learning regression, the study evaluated the performance of an embedded solution in comparison to a reference laboratory grade force plate. While insoles were validated in the context of gait, few studies investigated their accuracy in estimating ground reaction forces and moments for rehabilitation exercises with both feet on the ground. Thus, popular ankle and hip strategies, squat and hula hoop excercices were investigated. The estimation accuracy was reported with a low average error of $1.6 \pm 0.3\%$ of the body weight and $1.2 \pm 0.3\%$ of the body weight times the body height along with a moderate correlation when using solely features extracted from insoles measurements. These results demonstrated the possibility of using embedded solutions to estimate the full ground reaction wrench if the learning process was applied for each specific task separately.**

I. INTRODUCTION

Accurate estimation of Ground Reaction Forces and Moments (GRFM) is crucial for dynamical biomechanical analyses in rehabilitation [1], sport [2], and industrial ergonomics [3] applications. While walking is one of the most studied task in rehabilitation and human motor control, it is a highly specific task as the double support phase is very short. Assessing and understanding GRFM in movements with both supports held on the ground such as squats [4], hula hoop exercises [5] or hip-ankle balancing strategies [6] is also of great interest. These tasks are popular in rehabilitation as they engage the entirety of the human locomotor apparatus and represent disinct phases of many daily life activities [7], [8]. The gold standard system for GRFM measurement is a laboratory-grade force plate. Despite their high accuracy, precision, and ability to measure the full 6D GRFM, force plates provide wrench measurements in stationary given locations. Similarly, instrumented treadmills or the rare commercially available shoes embedding a 6D force sensor [9] can be seen as alternative ways to measure GRFM with an increased workspace. Yet, these methods do not allow for a fully ecological analysis of human motion.

To enable force measurements outside of a laboratory setting, numerous wireless insoles have been proposed over the last decade [10], [11], [12], [13]. Embedded insoles can be categorized as either force-sensing insoles, providing only the vertical force and, in a few studies [14], [15], [16], the two moments in the sagittal and frontal planes, or pressure-sensing insoles that measure plantar pressure distribution and magnitude. Validation studies conducted on force sensor insoles primarily focused on activities with minimal double support phases such as walking, running [17], [18], and jumping [17], [19]. Burns et al. [17] compared force sensing insoles with an instrumented treadmill during walking reporting an average Root Mean Square Error (RMSE) of 40N and a Pearson correlation coefficient r of 0.89 for the estimation of vertical force. Similarly, Braun et al. [20] validated pressure wireless insoles against treadmill measurements finding a RMSE on the vertical force of 36.3N with a correlation of > 0.994. Recently, Cudejko et al. [21] validated pressure insoles during squats and sit-to-stand movements involving prolonged double support phases. In comparison to force plate-measured vertical force and center of pressure, they reported an average RMSE of at least 100N and 1.5cm, respectively. These results underscored the challenge that commercially available pressure insoles face in estimating the GRFM in continuous double support movements.

Thus, to enhance insoles' performances, several studies employed machine learning techniques. For instance, Oubre et al. [15] used a Random Forest Regression (RFR) model to estimate the vertical force and the center of pressure from one low-cost instrumented insole with 6 force-sensitive resistor sensors during walking, along with an additional knee angle measurement system. They reported average RMSE of 66N for the vertical force and of 1cm for the center of pressure. However, they only validated one insole during walking trials and did not estimate the full set of GRFM. Similarly, Duong et al. [22] implemented deep neural networks to predict the center of pressure using custom instrumented insoles featuring an Inertial Measurement Unit (IMU) and 8 force-sensitive resistor arrays. Both healthy and pathological participants were asked to walk while performing three different tasks to construct a dataset. Bidirectional long short-term memory networks were trained on more than ten thousands walking cycles. Results showed an average RMSE of 1.2cm on center of pressure estimated when compared to force plate. In addition, Bergamo et al. [23] studied the performances of three machine/deep learning models, including a convolutional neural network, a fully connected network and a linear regressor, to reconstruct 3D GRF for post-stroke

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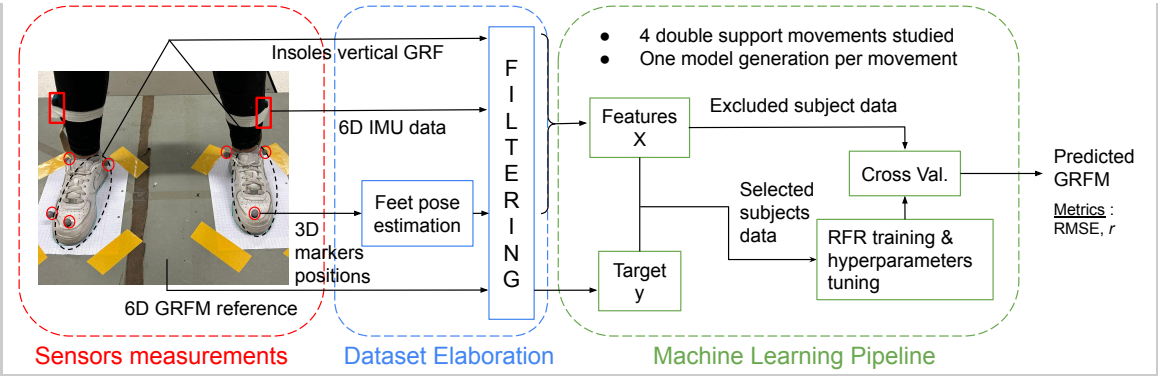

Fig. 1: Overview of the proposed Random Forest Regressor (RFR) for GRFM estimation algorithm.

patients using pressure insoles during walking cycles. They compared their results using an instrumented treadmill and found that the convolutional neural network-based approach achieved the best performances, with estimation errors as low as $0.75 \pm 0.24\%$, $1.13 \pm 0.54\%$, and $4.79 \pm 3.04\%$ of Body Weight (BW) for the medio-lateral, antero-posterior, and vertical GRF components, respectively. All the models also correlated strongly with the reference, with a $r > 0.80$.

To the best of our knowledge, all the studies using machine/deep learning algorithms train and validate their approach for a specific task. Mainly, they focused on studying movements with short double support phases and low shear forces like walking, running or jumping to estimate a reduced set of the GRFM or the center of pressure. However, double stance support movements are widely used in rehabilitation, and still need to be investigated. The use of machine learning algorithms coupled with instrumented insoles in this context has yet to be fully assessed. Consequently, the main contribution of this paper is to assess the possibility of accurately estimating the full 6D GRFM from embedded insoles using machine learning algorithms in the context of continuous double support rehabilitation movements.

II. METHODS

A. Sensors measurements

Different type of sensors were used in this study. GRFM reference measurements were collected using a commercially available laboratory-grade force plate (AMTI OR6 Series). The accurate positions of both feet relative to a universe frame R_0 were acquired using a marker-based motion capture system composed of 22 cameras (Vero v2.2, Vicon Nexus v2 [24], Oxford, UK). The marker set used to retrieve the left/right foot 3D positions $\mathbf{p}_l^0/\mathbf{p}_r^0$, as well as their 3D Euler angles rotations $\mathbf{r}_l^0/\mathbf{r}_r^0$, consisted of 4 markers for each foot, placed at the heel, second proximal phalange, lateral maleollus, and medial maleollus. For the force plate, the components of the GRF were denoted as Antero-Posterior (AP), Medio-Lateral (ML) and Vertical (V) while those of the GRM were denoted as Sagittal (S), Frontal (F) and Transverse (T). Embedded insoles loadsol® pro (Novel GmbH, Germany) were set up in each participant's shoe with the insole IMU mounted on the subject shin. Each insole (see Fig. 2.b) integrates force capacitive sensors located in three areas, one at the heel providing the vertical force F_{hee}, and two at the medial and lateral front parts of the foot, measuring the vertical forces F_{med} and F_{lat}, respectively. The full vertical forces measured by each insole were denoted as F_{full}. Additionally, the insoles feature an IMU providing 3D gyroscope and 3D accelerometer data: ω_x, ω_y, ω_z, a_x, a_y, a_z.

B. Datasets

Each dataset included the 6D reference force plate measurements for training along with insoles measurements that consisted of accelerometer and gyroscope data, the vertical force associated with the three areas of the insole, and the full vertical force. A column containing the weight W of each subject was added for better prediction scaling. All raw measurements underwent preprocessing and filtering using a fifth-order zero-phase lag Butterworth filter with cutoff frequency at 10Hz. The targets and features selected to train the model are outlined in Table I.

C. RFR modelling

Machine learning models were trained to predict GRFM using features data, which were preprocessed as detailed in section II-B. Fig. 1 provides an illustrative summary of the proposed algorithm. Two models were trained to estimate each axis of GRFM using RFR. One model, denoted as RFR_A used all the features presented in Table I, including insoles forces and IMU data, positions and orientations of both feet and the subject weight. The second, denoted as RFR_{IS} utilized features exclusively from the insoles. The performances of these two models were compared to those obtained using a Least Squares linear regressor referred to as LS and to the data measured directly by the insoles denoted as IS. RFR is an ensemble machine learning algorithm suited for regression tasks. It builds multiple decision trees during training, each trained on a random subset of samples and features. Thanks to techniques like random feature selection and bootstrap aggregating, RFR mitigates overfitting, enhances inter-subject generalization, and ensures robust predictions. It is known to account for non linear evolution

TABLE I: Features and targets used for the training

-	Sensor	Type of measurement
Targets y	Force plate	AP[N], ML[N], V[N], S[N.m], F[N.m], T[N.m]
Features X	Insoles	F_{hee}[N], F_{lat}[N],F_{med}[N], F_{full}[N], ω_x, ω_y, ω_z, a_x, a_y, a_z
	Optical motion capture	$\mathbf{p}_l^0$[m], $\mathbf{r}_l^0$[rad], $\mathbf{p}_r^0$[m], $\mathbf{r}_r^0$[rad]
	-	Subject Weight W[kg]

in the measurements, which is practical when a force sensor drift can occur over time. In addition, the features were not required to be scaled, allowing for the direct input of insoles measurements. Here, as the model had to predict 6D GRFM, a multi output regressor based on RFR was implemented using the scikit-learn library [25].

Cross-validation involved training the model on four subjects and validating it by excluding the remaining subject at a time until all subjects were assessed. To optimize the hyperparameters of the RFR, a grid search procedure relying on the RMSE metric was set up.

$$C = \begin{cases} \text{'n\_estimators'} \in \{50, 100, 200\}, \\ \text{'max\_depth'} \in \{10, 20, 30\}, \\ \text{'min\_samples\_split'} \in \{2, 5, 10\} \end{cases}$$

was denoted as the set of hyperparameters range for this study, where 'n_estimators' corresponded to the number of trees of the forest, 'max_depth' was the decision tree depth and 'min_samples_split' was the minimum number of samples required to split an internal tree node. In this study, the optimal hyperparameters $\hat{\theta} \in C$ resulting from the grid search were:

$$\hat{\theta} = \begin{pmatrix} \text{'n\_estimators'} = 100 \\ \text{'max\_depth'} = 10 \\ \text{'min\_samples\_split'} = 5 \end{pmatrix}$$

III. EXPERIMENTAL SETUP

Three healthy female and two healthy male participants (61 ± 9kg, 24 ± 1years, 1.68 ± 0.10m) were asked to perform four different tasks after giving their informed consent: squatting, hip and ankle balancing, and hula hoop exercises wearing force sensing insoles directly set between their socks and their everyday shoes soles. For each task, each subject performed three trials in different orders: one carrying no load, one with an additional load of 5kg and one with an additional load of 10kg. The additional load was put in a backpack that the participant carried on his/her back. The trials were conducted on the reference force plate and data acquisition was synchronized across all measurements modalities. During the trials, participants ensured that their feet remained at the exact same positions, indicated by two areas drawn on the force plate. The entirety of both feet remained in contact with the ground throughout the whole experiment. Reflective markers were placed on 4 anatomical landmarks on both the left and right foot (see section II-A).

IV. EXPERIMENTAL VALIDATION

The GRFM measured by the force plate served as a reference to calculate RMSE and *r* to assess the performance of the different regression models presented in section II-C

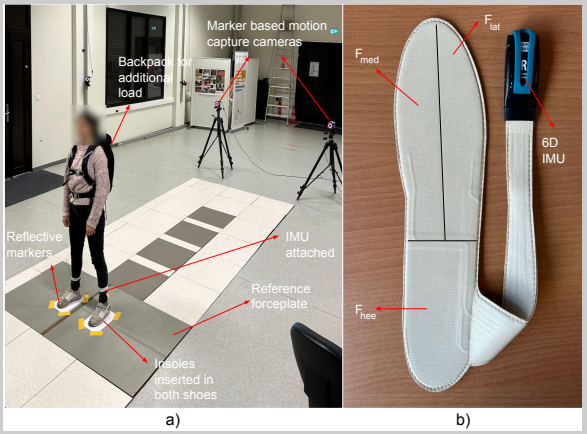

Fig. 2: Experimental setup a) and insoles measurements b).

in estimating GRFM over the cross-validation trials. Cross-validation results for the different models on the four different movements are provided in Tables II, III, IV and V, for squats, hip balancing strategy, ankle balancing strategy, and hula hoop, respectively. A graphical representation for one of the subjects is also provided in Fig. 3. Furthermore, for IS modality, only the results of V, S and F were investigated as the insoles do not provide shear forces.

Across all investigated movements and quantities, the models based on RFR significantly outperformed the LS model, and the insoles data. The average RMSE of GRF and GRM were 8.8 ± 1.4N and 12.2 ± 2.4N.m for RFR$_A$, 9.6 ± 1.6N and 12.2 ± 2.5N.m for RFR$_{IS}$, 35.1 ± 2.5N and 150.9 ± 7.6N.m for LS, and 77.2 ± 24.7N, 25.5 ± 3.3N.m for IS, respectively. When normalizing the GRF by the participant's BW, and the GRM by the participant's BW times his Body Height (BH), the results were of 1.5 ± 0.2%BW and 1.2 ± 0.2%BW.BH for RFR$_A$, 1.6 ± 0.3%BW and 1.2 ± 0.3%BW.BH for RFR$_{IS}$, 5.9 ± 0.4%BW and 15.0 ± 0.8%BW.BH for LS, and 12.9 ± 4.1%BW, 2.5 ± 0.3%BW.BH for IS, respectively. The average values of *r* were 0.61 ± 0.11, 0.59 ± 0.11, 0.66 ± 0.09, and 0.49 ± 0.10, for RFR$_A$, RFR$_{IS}$, LS, and IS, respectively. These results highlight the improved accuracy obtained through RFR approaches, demonstrating a significant decrease in RMSE. Furthermore, the different *r* values obtained show moderate associations between the GRFM estimated by all the models and the force plate reference data, an aspect further explored in the next section.

V. DISCUSSION

This study evaluated the accuracy of GRFM estimation based on a machine learning regression model trained on embedded insoles measurements, focusing on continuous

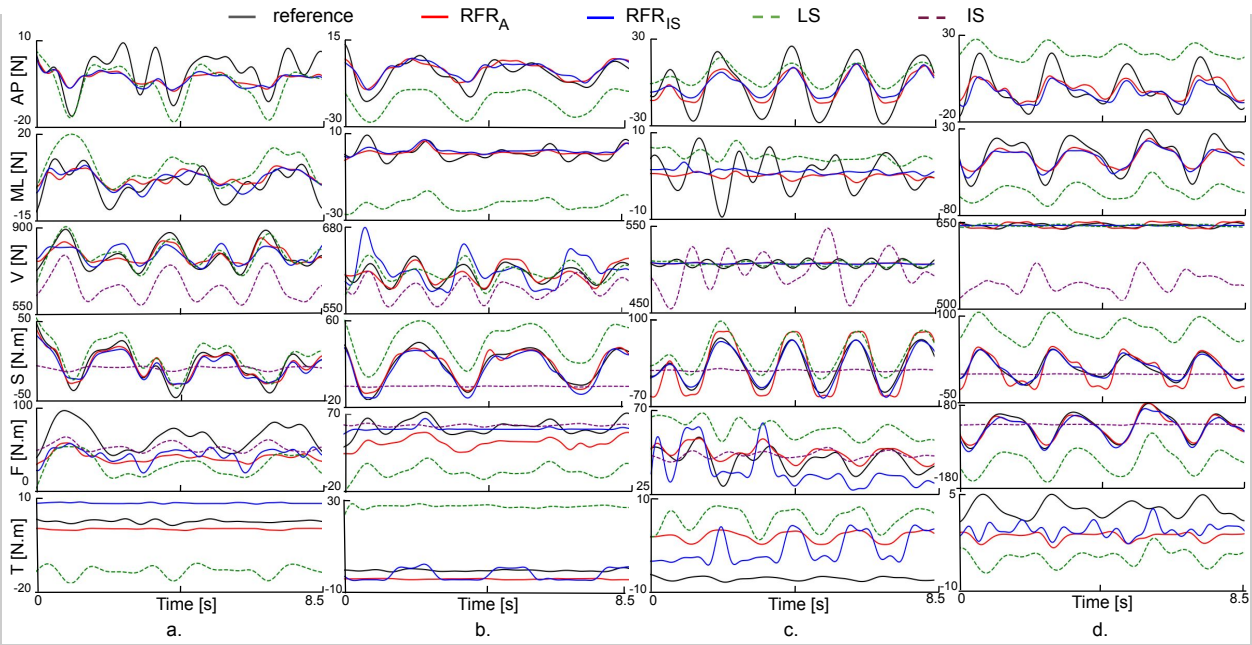

Fig. 3: GRFM measured from the force plate (black), estimated from RFR_A (red), RFR_{IS} (blue), LS (dashed green) and IS (dashed purple) for one subject during a squat trial (a), a hip (b) and ankle (c) balancing trial and a hula hoop exercise (d).

TABLE II: Cross validation of GRFM predicted by the models compared to force plate measurements, during squats trials.

	RMSE				r			
-	RFR_A	RFR_{IS}	LS	IS	RFR_A	RFR_{IS}	LS	IS
AP	5.6 ± 1.1N	5.4 ± 0.9N	25.5 ± 1.8N	-	0.45 ± 0.13	0.42 ± 0.08	0.57 ± 0.10	-
ML	4.1 ± 0.5N	3.8 ± 0.5N	22.3 ± 2.7N	-	0.48 ± 0.13	0.50 ± 0.08	0.59 ± 0.10	-
V	32.7 ± 5.4N	36.2 ± 6.4N	26.2 ± 2.5N	68.9 ± 21.1N	0.83 ± 0.08	0.80 ± 0.06	0.87 ± 0.05	0.94 ± 0.03
Mean	$\mathbf{14.1 \pm 2.3}$N	$\mathbf{15.1 \pm 2.6}$N	$\mathbf{24.7 \pm 2.3}$N	$\mathbf{68.9 \pm 21.1}$N	$\mathbf{0.60 \pm 0.11}$	$\mathbf{0.57 \pm 0.07}$	$\mathbf{0.68 \pm 0.06}$	$\mathbf{0.94 \pm 0.03}$
S	7.5 ± 1.9N.m	7.2 ± 1.6N.m	102.7 ± 7.5N.m	23.2 ± 3.1N	0.78 ± 0.09	0.87 ± 0.08	0.90 ± 0.06	0.38 ± 0.15
F	20.1 ± 2.3N.m	19.7 ± 2.4N.m	140.0 ± 6.5N.m	7.1 ± 1.8N.m	0.67 ± 0.08	0.54 ± 0.09	0.74 ± 0.10	0.56 ± 0.13
T	3.8 ± 1.8N.m	7.3 ± 2.3N.m	175.5 ± 6.5N.m	-	0.28 ± 0.17	0.27 ± 0.09	0.23 ± 0.18	-
Mean	$\mathbf{10.5 \pm 2.0}$N.m	$\mathbf{11.4 \pm 2.1}$N.m	$\mathbf{139.4 \pm 6.8}$N.m	$\mathbf{15.2 \pm 2.4}$N.m	$\mathbf{0.58 \pm 0.11}$	$\mathbf{0.56 \pm 0.09}$	$\mathbf{0.62 \pm 0.11}$	$\mathbf{0.47 \pm 0.14}$

TABLE III: Cross validation of GRFM predicted by the models compared to force plate measurements, during hip balancing trials.

	RMSE				r			
-	RFR_A	RFR_{IS}	LS	IS	RFR_A	RFR_{IS}	LS	IS
AP	4.6 ± 0.5N	4.3 ± 0.5N	17.2 ± 1.2N	-	0.65 ± 0.11	0.63 ± 0.14	0.75 ± 0.08	-
ML	3.7 ± 0.7N	3.7 ± 0.6N	102.6 ± 2.8N	-	0.40 ± 0.18	0.24 ± 0.22	0.50 ± 0.07	-
V	9.6 ± 1.9N	19.2 ± 3.3N	14.8 ± 2.3N	71.5 ± 29.2N	0.58 ± 0.16	0.31 ± 0.26	0.61 ± 0.10	0.70 ± 0.07
Mean	$\mathbf{6.0 \pm 1.0}$N	$\mathbf{9.1 \pm 1.5}$N	$\mathbf{44.9 \pm 2.1}$N	$\mathbf{71.5 \pm 29.2}$N	$\mathbf{0.54 \pm 0.15}$	$\mathbf{0.39 \pm 0.21}$	$\mathbf{0.62 \pm 0.08}$	$\mathbf{0.70 \pm 0.07}$
S	8.5 ± 2.3N.m	7.1 ± 2.3N.m	338.6 ± 11.6N.m	27.2 ± 3.4N.m	0.95 ± 0.01	0.95 ± 0.02	0.97 ± 0.02	0.71 ± 0.08
F	12.7 ± 2.0N.m	14.8 ± 2.0N.m	467.4 ± 9.8N.m	8.7 ± 1.9N.m	0.55 ± 0.14	0.51 ± 0.22	0.61 ± 0.17	0.17 ± 0.09
T	5.2 ± 2.7N.m	8.7 ± 2.9N.m	289.3 ± 5.3N.m	-	0.19 ± 0.22	0.30 ± 0.18	0.29 ± 0.19	-
Mean	$\mathbf{8.8 \pm 2.3}$N.m	$\mathbf{10.2 \pm 2.4}$N.m	$\mathbf{273.8 \pm 8.9}$N.m	$\mathbf{18.0 \pm 2.7}$N.m	$\mathbf{0.56 \pm 0.12}$	$\mathbf{0.59 \pm 0.14}$	$\mathbf{0.62 \pm 0.13}$	$\mathbf{0.44 \pm 0.09}$

TABLE IV: Cross validation of GRFM predicted by the models compared to force plate measurements, during ankle balancing trials.

	RMSE				r			
-	RFR_A	RFR_{IS}	LS	IS	RFR_A	RFR_{IS}	LS	IS
AP	7.6 ± 1.1N	7.3 ± 0.8N	56.9 ± 1.8N	-	0.87 ± 0.03	0.91 ± 0.02	0.90 ± 0.02	-
ML	4.0 ± 1.3N	3.5 ± 0.8N	6.5 ± 1.3N	-	0.36 ± 0.10	0.29 ± 0.24	0.47 ± 0.12	-
V	3.0 ± 0.5N	3.8 ± 0.7N	2.4 ± 0.5N	52.0 ± 7.8N	0.49 ± 0.19	0.32 ± 0.2	0.61 ± 0.08	0.21 ± 0.11
Mean	$\mathbf{4.9 \pm 1.0}$N	$\mathbf{4.9 \pm 0.8}$N	$\mathbf{21.9 \pm 1.2}$N	$\mathbf{52.0 \pm 7.8}$N	$\mathbf{0.57 \pm 0.11}$	$\mathbf{0.51 \pm 0.15}$	$\mathbf{0.66 \pm 0.07}$	$\mathbf{0.21 \pm 0.11}$
S	14.2 ± 1.6N.m	8.5 ± 2.3N.m	27.3 ± 1.8N.m	42.8 ± 3.1N.m	0.97 ± 0.01	0.98 ± 0.01	0.99 ± 0.01	0.94 ± 0.02
F	20.3 ± 3.6N.m	22.2 ± 4.0N.m	93.2 ± 3.5N.m	8.9 ± 1.4N.m	0.54 ± 0.09	0.56 ± 0.07	0.74 ± 0.10	0.19 ± 0.23
T	5.3 ± 2.6N.m	8.6 ± 2.6N.m	77.1 ± 3.5N.m	-	0.40 ± 0.30	0.56 ± 0.12	0.45 ± 0.16	-
Mean	$\mathbf{13.3 \pm 2.6}$N.m	$\mathbf{13.1 \pm 2.9}$N.m	$\mathbf{65.9 \pm 2.9}$N.m	$\mathbf{25.9 \pm 2.2}$N.m	$\mathbf{0.64 \pm 0.13}$	$\mathbf{0.70 \pm 0.05}$	$\mathbf{0.73 \pm 0.09}$	$\mathbf{0.57 \pm 0.08}$

TABLE V: Cross validation of GRFM predicted by the models compared to force plate measurements, during hula hoop trials.

	RMSE				r			
-	RFR_A	RFR_{IS}	LS	IS	RFR_A	RFR_{IS}	LS	IS
AP	10.2 ± 0.7N	6.8 ± 0.5N	18.4 ± 2.0N	-	0.80 ± 0.05	0.85 ± 0.04	0.82 ± 0.06	-
ML	14.7 ± 2.5N	16.0 ± 2.5N	124.3 ± 10.8N	-	0.91 ± 0.02	0.90 ± 0.03	0.84 ± 0.04	-
V	5.2 ± 0.9N	4.7 ± 1.3N	4.4 ± 0.8N	166.4 ± 40.8N	0.27 ± 0.15	0.20 ± 0.22	0.34 ± 0.25	0.15 ± 0.08
Mean	$\mathbf{10.0 \pm 1.4}$**N**	$\mathbf{9.2 \pm 1.4}$**N**	$\mathbf{49.0 \pm 4.5}$**N**	$\mathbf{166.4 \pm 40.8}$**N**	$\mathbf{0.66 \pm 0.07}$	$\mathbf{0.65 \pm 0.10}$	$\mathbf{0.66 \pm 0.12}$	$\mathbf{0.15 \pm 0.08}$
S	21.3 ± 1.1N.m	8.5 ± 1.0	77.8 ± 8.4N.m	29.7 ± 2.2N.m	0.85 ± 0.02	0.94 ± 0.02	0.98 ± 0.01	0.61 ± 0.26
F	19.0 ± 3.4N.m	24.3 ± 3.7	244.4 ± 23.7N.m	56.3 ± 3.6N.m	0.97 ± 0.01	0.97 ± 0.01	0.96 ± 0.02	0.24 ± 0.10
T	8.6 ± 2.9N.m	9.7 ± 3.1N.m	71.4 ± 3.1N.m	-	0.37 ± 0.18	0.25 ± 0.24	0.25 ± 0.19	-
Mean	$\mathbf{16.3 \pm 2.5}$**N.m**	$\mathbf{14.2 \pm 2.6}$**N.m**	$\mathbf{124.5 \pm 11.7}$**N.m**	$\mathbf{43.0 \pm 5.8}$**N.m**	$\mathbf{0.73 \pm 0.07}$	$\mathbf{0.72 \pm 0.09}$	$\mathbf{0.73 \pm 0.07}$	$\mathbf{0.42 \pm 0.18}$

double support movements commonly used in rehabilitation. A comparative analysis was conducted to explore the application of RFR for GRFM estimation across various movements with different plantar forces distributions. Additionally, the study aimed to assess the accuracy of GRFM reconstruction using embedded insoles, that are not yet able to retrieve the full 6D components of the external wrench. Existing literature [15], [23], [26] evaluated the GRF reconstruction in single support movements, or with very short double support phase such as walking, using methods and metrics similar to those employed in this study. For instance, Oubre et al. [15] used the same RFR method, but with more low cost insoles, resulting in two times less accurate vertical force predictions. Two other studies [23], [26] using higher-quality insoles reported results equivalent to those of the present study. Deep learning models [23], [26] obtained GRF estimation accuracy in terms of %BW similar to the findings in section IV. When a Gaussian process regression was used during walking [26], results for AP, ML and V were much worse than the present study with reported average normalized RMSE of 17.5 ± 3.5%BW, 6.9 ± 1.0%BW, and 5.2 ± 2.2%BW, respectively. Moreover, results concerning the GRM were not found in the aforementioned papers.

The results presented in tables II, III, IV, and V as well as in Fig.3 highlighted a moderate to medium correlation between predicted and reference measurements, which can be explained by multiple factors. First, two movement categories were identified, those where V was predominant, such as squats and those with large shear forces like in balancing strategies or hula hoop exercises. In the case of squats, V showed the strongest correlation between the predictions from insoles and the force plate measurements, indicating that insoles captured the main aspects of the GRF distribution found in V. For other movements, either AP, or ML, or both, presented the strongest correlation with a relatively low r for V. It is not entirely clear what is happening with the insole sensors but likely their lateral deformation and the relative sliding of the feet inside the shoe altered the insoles' behavior.

Furthermore, during all trials a non-linear sensor drift, especially high when shear forces were large, was observed in the measured V. The goal of our paper was not to investigate the specific drift of the used insole but rather to assess the ability of machine learning to compensate for it. The presence of this drift means that, for example, the total estimated weight during static phases at the beginning and at the end of the motion was not the same. It is visible in Fig.3.d that for the hula hoop task, the IS vertical force shown in dashed purple is much lower than the actual total weight, while it was correct at the beginning of the motion. Again the exact mechanical/electronic phenomenons at play are unclear but the proposed RFR method was able to compensate for these inaccuracies. Conversely, the LS model was less robust, probably due to the non-linearity of the drift, explaining the large RMSE in the GRM prediction. The LS model attempted to find a solution that harmonized between subjects with varying sensors drifts, and since the number of subjects in this study was relatively small, there were limited opportunities to smooth out the prediction. Regarding GRM, it was challenging for all models to accurately estimate T because it was usually very small as it is not significant in continuous double support movements. For moments in the other two directions, they were fairly well estimated, especially for S, which showed the strongest correlation. This was associated with the good estimation of AP, which is unsurprising since all studied movements involved displacements of the center of pressure in the frontal plane. The center of pressure position was not explicitly given in the results, but it can be deduced from V, S and F which were quite accurately estimated.

Interestingly, both RFR_A and RFR_{IS} models achieved almost the same level of accuracy across all trials. In other words, even if the foot positions were not perfectly defined (indicated by two areas drawn on the floor), the estimation of the GRM remained satisfactory. This result is corroborated by others [15], which stated that the set of features composed of insoles force measurements as well as IMU measurements were sufficient to properly estimate the GRFM. The main limitations of the present study remain in the small number of subjects that did not realistically allow for broader generalisation, resulting in a dataset that did not reflect the entirety of the population. This led to models that were trained insufficiently to achieve a stronger correlation with the reference data. Furthermore, another shortcoming of the study was that a different model was trained for each different movement studied. Indeed, it was not possible to find a unique model able to discriminate between all the different force distributions induced by the different movements as well as adapting to the subject differences in weight and plantar shapes. However, having a regression

model per type of movement is a plausible hypothesis for prescribed rehabilitation tasks. Moreover, it is also possible to classify the movement from insoles data beforehand [27]. Another alternative to enhance performance could be to try other types of models like the recently released physics informed neural network [28], which can take into account specific knowledge about the physics of the problem to more accurately retrieve GRFM across different types of movements.

VI. CONCLUSIONS

In conclusion, this study aimed to achieve comprehensive 6D GRFM estimation by using embedded insole measurements and IMU data in conjunction with a RFR algorithm. The primary objectives included exploring the benefits of machine learning models in addressing this regression problem and evaluating the accuracy of estimating GRFM for double support movements, an aspect hitherto unexplored in the existing literature.

The findings emphasized a notable enhancement in the accuracy, as measured by RMSE, of GRFM estimation by RFR algorithms, as opposed to a linear model or measurements provided by the insole manufacturer. Moreover, the study demonstrated that the combination of insole and IMU measurements sufficed for estimating GRFM with an acceptable level of accuracy. However, anticipations for improvements lie in the correlation between estimated and reference measurements. Challenges arose due to sensors drift and unconventional plantar force distributions inherent in continuous double support movements. The RFR models found it difficult to maintain a satisfactory correlation rate for all components of the GRFM wrench across various movements studied. Looking ahead, future studies incorporating diverse deep learning models and different types of insoles will be pivotal in optimizing GRFM estimation for continuous double support movements.

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