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# Estimation of ground reaction forces in rugby scrummaging using instrumented insoles and machine learning

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**Abstract**—Scrummaging is a critical and intense phase of rugby union, involving considerable forces and presenting the highest risk of injury during a rugby game. Despite its importance as an indicator of game success, the forces generated by individual players within the scrummaging have yet to be investigated. Studies have mainly focused on individual and collective pushing forces against scrummaging machines, with little attention to the ground reaction forces. However, these ground reaction forces are essential for dynamic biomechanical analyses, particularly in sports performance and reduction of injury risks. While instrumented insoles have been validated for gait and movements involving primarily vertical forces, their application in rugby scrummaging remains unexplored. The objective of this paper was to develop a method to estimate the three components of ground reaction forces, using a combination of instrumented insoles and machine learning. A Long-Short-Term-Memory (LSTM) neural network was trained to estimate ground reaction forces from data collected by instrumented insoles and inertial measurement units. Thirteen participants were evaluated to validate the method, performing thrusts against an individual scrum machine with feet on force plates. The average root mean square errors over all subjects between the estimated forces and the reference force plate data were  $58.4 \pm 12.0$ N on the Antero-Posterior axis,  $21.2 \pm 2.0$ N on the Medio-Lateral axis, and  $61.1 \pm 9.2$ N on the vertical axis. These findings demonstrate the potential of using instrumented insoles to accurately estimate the ground reaction forces, particularly the thrust force, of rugby players during scrummaging.

**Keywords**—*biomechanics, sports, performance, AI*

## I. INTRODUCTION

Rugby scrummaging is a method used to restart play following minor infringements, aimed at retaining or gaining possession of the ball. This critical and high-intensity phase of rugby union involves significant force generation and poses the greatest injury risk during a match. Moreover, scrum performance is a key indicator of game success, with the number of scrums won being positively correlated with match outcomes [1,2].

A key determinant of scrum success is the horizontal force exerted by the entire pack, especially during the sustained phase [3]. Previous studies have measured both individual [4-6] and collective [7, 8] forces during scrummaging, mainly using instrumented scrummaging machines. However, these machines tend to overestimate the forces due to the rigidity of their structure [9] and are inadequate for capturing the contribution of each player within the scrum. This is critical, as only 65% of the sum of individual player efforts is typically translated into collective pack force [10]. In addition, under these conditions, the measured forces typically reflect only the horizontal component of the pushing force. However, the vertical and lateral components are crucial for maintaining stability during scrummaging [4]. To address this, Du Toit et al. [11] used force plates to measure the three-dimensional Ground Reaction Forces (GRF) of each player in a scrum while the entire pack was pushing against a machine. Despite this, such methods are unsuitable for capturing forces during live scrummaging, where significant differences exist compared to machine-based scrums. To bridge this gap, some researchers have employed pressure sensor pads placed on the shoulders of all eight players to measure individual horizontal forces during live scrummaging [8, 11, 12]. However, these pads tend to underestimate forces as they do not cover the full contact area between a player's shoulder and another player [11, 12].

To address the challenge of measuring individual GRF in real-world conditions, new wearable systems, such as instrumented insoles, have been developed. These systems are primarily used for applications involving vertical GRF, as they typically measure the normal force exerted on the insole. Recent studies have employed machine learning techniques to estimate the three components of GRF using data from instrumented insoles [13-16]. While the specific machine learning models vary, the activities studied predominantly involve cyclic and repeatable movements like walking or running. Among the various models, Long-Short-Term-Memory (LSTM) networks, which can capture the temporal

dependencies of movement data, appear particularly well-suited for this application.

To date, no study has investigated the prediction of the three components of GRF from instrumented insoles and using machine learning during rugby scrummaging. Thus, the objective of this study was to develop a method for estimating the individual three-dimensional GRF during rugby scrummaging, using instrumented insole data and machine learning. In this context, we hypothesize that better knowledge of the individual pushing forces could lead to better scrum management from the trainers to find the combination that produces the greatest thrust force.

## II. MATERIAL AND METHODS

### A. Materials and protocol

Thirteen healthy participants were recruited for this study (3 females, 10 males; age: 26 +/- 6 years; height: 174 +/- 6.2 cm; weight: 71.6 +/- 11.7 kg). All participants were free from lower limb injuries and were recreationally active subjects with no specific experience in rugby scrummaging. They wore non-standardized rugby shoes during the experiment. Each participant provided written informed consent before participation. The experimental protocol was approved by the Ethical Committee of the University of Toulouse.

Participants wore commercial instrumented insoles (Loadsol Pro®, Novel, Munich, Germany) inside their shoes. Each insole was equipped with capacitive force sensors measuring normal forces applied perpendicularly to the sensor surface. The design of the insole divided the resultant forces into three distinct areas: heel, medial, and lateral. An integrated inertial unit (IMU) was attached to the shoelaces on each foot (Fig. 1.b). Data from the insoles and IMU were recorded synchronously at 200Hz via the mobile application Loadapp (Novel, Munich, Germany). Two force plates (AMTI OR6 Series) covered with artificial turf (Fig. 1.a) recorded GRF at 1000Hz. Data from the force plates served as the reference data.

Before the experiment, participants completed a self-warm-up and practiced pushing against a scrum machine (Fig. 1.a). The insoles were calibrated according to the manufacturer's instructions: after walking a few steps, participants stood still and lifted one foot at a time. Calibration was successful when the displayed body weight on the application matched the actual body weight within a

margin of error of  $\pm 10$  N. If discrepancies were found, the calibration was repeated until the displayed body weight matched the participant's actual body weight.

Each participant performed four pushing trials, lasting between 30 and 40 seconds, against a fixed scrummaging machine, with brief foot repositioning as needed. Before and after pushing, participants were asked to tap their right foot on the force plate to synchronize insoles and force plate data post-experiment. Participants were instructed to maintain a straight back, parallel to the ground, with hip, knee, and ankle angles at approximately  $90^\circ$ . Between pushes, the insoles were removed from the rugby shoes and participants were given a five-minute rest.

### B. Data pre-processing

A total of 50 valid pushes across the thirteen participants were analyzed, with 3 or 4 valid trials per participant.

Insole missing data were gap-filled using cubic interpolation at a frequency of 200Hz. Force plate data were resampled at 200Hz and synchronized with the insole data. This was achieved by comparing the vertical GRF from the force plates with the insole force data and performing cross-correlation around the peak effort corresponding to the moment when participants tapped their right foot on the force plate before pushing. Data from the left and right insoles and inertial units were already synchronized during recording by the Loadapp.

Data outside the interval between the first and the second right foot strikes on the force plate were removed to retain only the data relating to the pushing.

The force data recorded from the different areas of the insoles, and inertial data given by the 3D accelerometer and the 3D gyroscope of each insole constituted the input data. The target data consisted of the three components of the GRF measured by the two force plates. Both input and target data were filtered using a fourth-order low-pass Butterworth filter with a cut-off frequency of 5Hz. The body weight (in Newtons) and the shoe size of each participant were added to the input data without filtering.

Input and target data were normalized and divided into three datasets: training, validation, and test datasets. The test dataset comprised data from two trials of one participant while the remaining trials were included in the training dataset. Data from the other participants were randomly

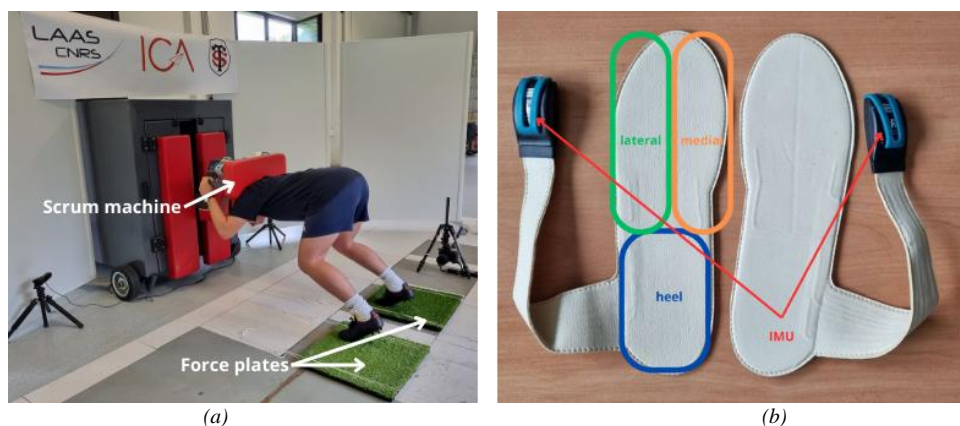


Fig. 1. Experimental setup (a) and instrumented insoles (b) used for this study.

split, with 80% allocated to the training set, and 20% to the validation set (Fig. 2).

### C. Model architecture and training

The neural network employed in this study was implemented using Pytorch [17]. It consisted of a LSTM layer, followed by a fully connected Multi-Layer Perceptron (MLP) layer with a Rectified Linear Unit (ReLU) activation function (Fig. 3). The network was trained using the Adaptive Moment Estimation (Adam) optimizer and a mean squared error (MSE) loss function. The hyperparameters considered included learning rate, weight decay, sequence length, LSTM hidden dimension, number of LSTM layers, and MLP hidden dimension. Various configurations of these hyperparameters were explored to identify the optimal model architecture, as detailed in Table 1.

To determine the optimal set of hyperparameters, a grid search procedure relying on the Root Mean Square Error (RMSE) and Pearson correlation coefficient ( $r$ ) between the predicted and reference values of each GRF component was set up.

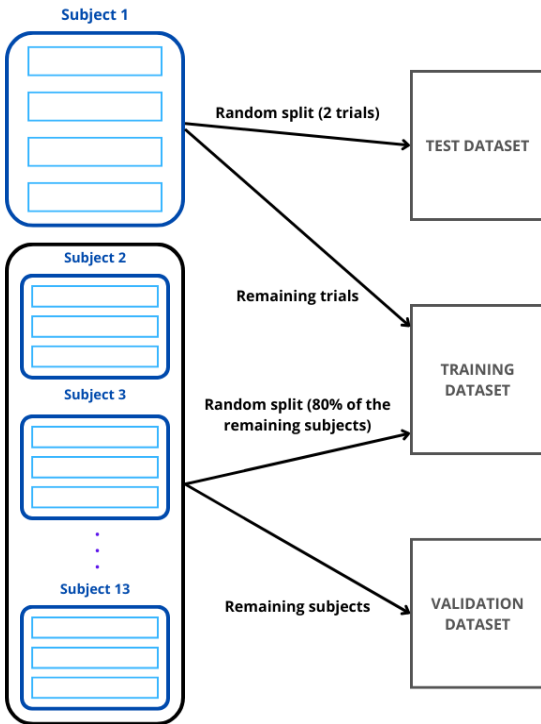


Fig. 2 Process of data division test, training, and validation datasets. The process was repeated thirteen times for each subject to enable cross-validation across all subjects.

TABLE I. VALUES OF THE TESTED PARAMETERS FOR THE LSTM AND THE MLP LAYER.

Parameters	Tested values
Learning rate	1e-4, 1e-6
Weight decay	1e-3, 1e-4
Sequence length	200, 400
Hidden dimension (LSTM)	64, 128
Number of layers (LSTM)	2, 3
Hidden dimension (MLP)	64, 128

Cross-validation was conducted using a leave-one-subject-out approach over thirteen iterations, corresponding to the number of subjects in the dataset. In each iteration, one subject was selected to feed the test dataset with two trials, as described previously, ensuring that all subjects were eventually evaluated.

### III. RESULTS

The optimal hyperparameters identified were:

- Learning rate: 1e-4
- Weight decay: 1e-3
- Batch size: 64
- Sequence length: 200
- Hidden dimension (LSTM): 64
- Number of layers (LSTM): 3
- Hidden dimension (MLP): 64

The model's performances were assessed by computing the mean RMSE and  $r$  over the two trials contained in the test dataset for each subject. The results are presented in Table 2.

The mean RMSE over all subjects were  $58.4 \pm 12.0N$  on the Antero-Posterior (AP) axis,  $21.2 \pm 2.0N$  on the Medio-Lateral (ML) axis, and  $61.1 \pm 9.2N$  on the vertical (V) axis.

The mean correlation coefficients  $r$  over all subjects were  $0.942 \pm 0.027$  on the AP axis,  $0.867 \pm 0.017$  on the ML axis, and  $0.808 \pm 0.042$  on the vertical axis.

The mean percentages of RMSE compared to the average resultant force over all subjects were  $6.8 \pm 1.3\%$  on the AP axis,  $2.5 \pm 0.2\%$  on the ML axis, and  $7.2 \pm 1.0\%$  on the vertical axis.

Fig. 4 shows the predicted GRF on both feet compared to the GRF measured by the force plates for one subject in the first 10 seconds of the trial.

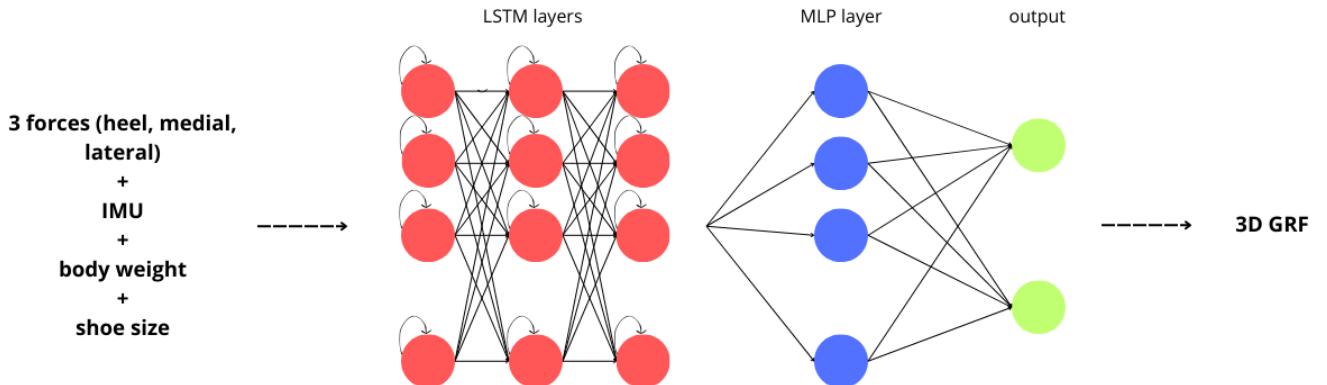


Fig. 3 Model architecture combining LSTM and MLP layers.

TABLE II. PERFORMANCES OF THE MODEL TRAINED FOR EACH SUBJECT.

	RMSE (N)			$r$			% RMSE compared to mean resultant force		
	AP	ML	V	AP	ML	V	AP	ML	V
<b>Subject 1</b>	56.5±10.7	27.3±1.8	65.6±3.3	0.912±0.017	0.828±0.059	0.752±0.030	8.0±1.2	3.9±0.4	9.3±0.1
<b>Subject 2</b>	70.9±6.2	21.1±0.6	64.9±15.9	0.932±0.008	0.785±0.009	0.764±0.071	9.1±0.6	2.7±0.0	8.3±1.9
<b>Subject 3</b>	118.3±23.2	35.0±6.4	92.4±15.6	0.913±0.044	0.836±0.021	0.813±0.021	10.2±1.8	3.0±0.6	8.0±1.2
<b>Subject 4</b>	48.8±8.1	17.6±0.5	71.0±6.2	0.960±0.015	0.794±0.020	0.733±0.030	6.8±1.5	2.5±0.2	9.8±1.3
<b>Subject 5</b>	64.6±26.4	27.4±2.3	80.0±17.5	0.980±0.009	0.900±0.030	0.903±0.016	6.1±2.4	2.6±0.3	7.6±1.6
<b>Subject 6</b>	63.4±16.8	28.5±1.0	57.0±3.4	0.951±0.023	0.692±0.012	0.802±0.045	7.0±1.6	3.2±0.2	6.3±0.1
<b>Subject 7</b>	73.0±5.7	24.0±4.7	76.3±7.4	0.936±0.016	0.925±0.013	0.843±0.028	7.1±0.8	2.4±0.4	7.4±1.0
<b>Subject 8</b>	78.2±3.6	24.4±0.8	53.5±0.1	0.813±0.132	0.809±0.005	0.579±0.082	11.2±0.5	3.5±0.1	7.6±0.0
<b>Subject 9</b>	75.7±42.1	25.5±2.5	86.3±30.6	0.913±0.076	0.857±0.025	0.675±0.135	8.2±4.5	2.8±0.2	9.3±3.2
<b>Subject 10</b>	25.0±4.0	10.2±1.1	34.8±2.9	0.987±0.001	0.945±0.013	0.874±0.048	4.4±0.6	1.8±0.1	6.2±0.4
<b>Subject 11</b>	44.6±1.3	19.4±4.1	59.7±12.6	0.976±0.005	0.948±0.011	0.887±0.013	4.8±0.1	2.1±0.4	6.5±1.3
<b>Subject 12</b>	19.0±4.2	6.2±0.1	22.8±1.5	0.984±0.001	0.975±0.002	0.940±0.011	3.3±0.9	1.1±0.0	4.0±0.2
<b>Subject 13</b>	21.4±3.7	9.5±0.4	29.8±2.5	0.989±0.004	0.975±0.006	0.935±0.021	2.7±0.7	1.2±0.1	3.7±0.7

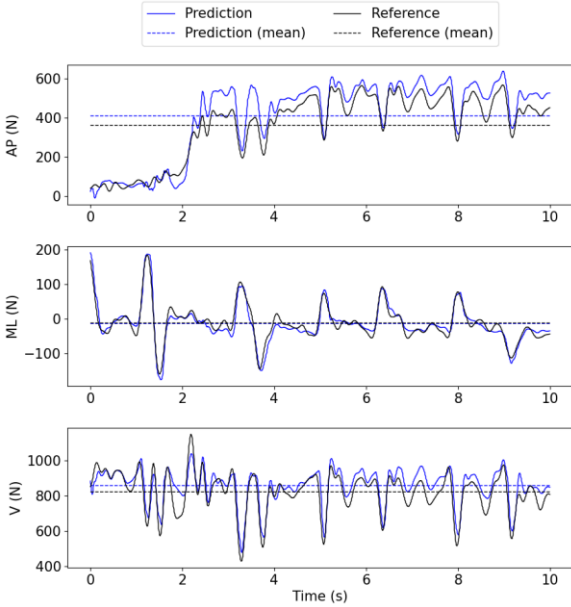


Fig. 4 GRF estimated from the LSTM (blue) and measured by the force plates (black) for one subject during scrummaging, on the Antero-Posterior (AP), Medio-Lateral (ML), and Vertical (V) axes.

#### IV. DISCUSSION

This study assessed the effectiveness of a LSTM neural network model in estimating the three components of ground reaction forces using data from instrumented insoles during rugby scrummaging.

In this study, personalized models were trained for each subject by incorporating thrust data from the subject evaluated into the training set. Honert et al. [18] demonstrated that the use of personalized models can significantly reduce prediction errors, lowering the mean error percentage from 7.7% to 2.9% on the vertical axis and from 8.0% to 5.2% on the AP axis. Additionally, training a

generalizable model typically requires a large and diverse dataset [19], which was not available in this study.

The results of this study are consistent with the order of magnitude reported in the literature, even for different activities. Kim et al. [20] estimated the three components of the GRF using uniaxial load cells during gait, reporting mean RMSE values on both feet of 15.5N (AP), 9.83N (ML), and 65.12N (V), with correlation coefficients of 0.96 (AP), 0.90 (ML), and 0.97 (V). Similarly, Kammoun et al. [16] reported mean RMSE values on both feet for gait of 36.49±2.07N (AP), 15.08±0.82N (ML), and 59.94±2.65N (V), along with mean correlation coefficients of 0.63±0.049 (AP), 0.75±0.32 (ML), and 0.978±0.002N (V). Both studies found higher RMSE values on the vertical axis, as GRFs are the largest in this direction during gait. In scrummaging, however, both the AP and vertical axes exhibit high GRF magnitudes, which explains why the RMSE on the AP axis in this study was similar to that of the vertical axis. The correlation coefficients obtained in this study were comparable to those reported by Kim et al. [20] and higher than those reported by Kammoun et al. [16].

While the results of this study are consistent with the order of magnitude reported in the literature, variations between subjects were observed. Subject 3 exhibited higher RMSE values on all axes compared to the mean across all subjects. However, despite the higher RMSE, this subject's correlation coefficients and percentage RMSE relative to the average resultant force were good across all axes. This discrepancy could be attributed to improper calibration or placement of the insoles in the rugby shoes. Conversely, several subjects (notably subjects 10, 12, and 13) showed particularly strong model performance, with RMSE values on all axes lower than the overall mean. One possible explanation is that these subjects generated lower resultant forces with less variability during the thrust phase, leading to reduced error. Regarding correlation coefficients, subject 6 (ML axis) and subject 8 (V axis) showed lower values compared to the mean over all subjects, which may be due to excessive slipping during the thrust phase.

Comparing the results of this study with those in the literature was challenging for two main reasons. First, most studies focus on evaluating GRF during cyclic activities such as gait or running. Kammoun et al. [16] highlighted that model performance is highly dependent on the specific activity the model is trained on. Second, many studies report their results as a percentage of RMSE relative to body weight [14, 15, 21], which is relevant for activities like gait or running, where vertical forces dominate. In contrast, scrummaging involves primarily GRF in the AP and V directions, making normalization by body weight less meaningful. Therefore, in this study, results were presented in terms of RMSE for each axis, as well as RMSE normalized by the average resultant force during the entire thrust. This approach was deemed more relevant for scrummaging and could be practically useful for trainers who may apply this method to evaluate GRF in real-world conditions.

This study has several limitations that should be acknowledged. First, it was conducted with recreationally active subjects, most of whom had little to no experience in rugby scrummaging. This lack of experience may have led to improper posture and increased slipping on the artificial turf, resulting in higher errors. Second, the subjects did not wear standardized shoes, even though [15] recommends doing so. This decision was made to simulate real-world conditions where players would wear their own rugby shoes, introducing variability in the measured GRF due to differences in footwear. Lastly, the instrumented insoles used in this study did not always perfectly fit the participants' shoe sizes. This mismatch may have led to lower measured forces and reduced accuracy in GRF estimation.

Despite this, results demonstrated that the proposed method can accurately measure 3D GRF individually and in-field, with an error percentage on all three axes relative to the mean resultant force below 8%. When combined with machine learning, instrumented insoles offer a reliable and practical tool for coaches to better understand player interactions in the scrum and identify the combination that generates the highest thrust force.

## V. CONCLUSION

In conclusion, this study demonstrated the potential of using instrumented insoles combined with machine learning to accurately estimate ground reaction forces of rugby players during scrummaging. Future work will focus on expanding the dataset to include junior and professional rugby players and exploring various machine learning models to enhance GRF estimation with instrumented insoles. Additionally, applying Statistical Parametric Mapping (SPM) could provide valuable insights by assessing model performance across the entire trial, helping to identify which phase of the thrust (impact or sustained) generates the most significant errors.

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