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Virginia Civeriati
Dipartimento di Elettronica, Informazione e Bioingegneria
Politecnico di Milano
Milan, Italy
virginia.civeriati@mail.polimi.it

Benito L. Pugliese
Department of Electronics and Telecommunications
Politecnico di Torino
Turin, Italy
bpugliese@mgh.harvard.edu

Carlo Carraro
Dipartimento di Elettronica, Informazione e Bioingegneria
Politecnico di Milano
Milan, Italy
carlo.carraro@mail.polimi.it

Giulia Corniani
Department of Physical Medicine and Rehabilitation
Harvard Medical School
Boston, MA, USA
gcorniani@mgh.harvard.edu

Federico Bauducco
Department of Physical Medicine and Rehabilitation
Harvard Medical School
Boston, MA, USA
fbauducco@mgb.org

Alessandra Angelucci
Dipartimento di Elettronica, Informazione e Bioingegneria
Politecnico di Milano
Milan, Italy
alessandra.angelucci@polimi.it

Andrea Aliverti
Dipartimento di Elettronica, Informazione e Bioingegneria
Politecnico di Milano
Milan, Italy
andrea.aliverti@polimi.it

Paolo Bonato
Department of Physical Medicine and Rehabilitation
Harvard Medical School
Boston, MA, USA
pbonato@mgh.harvard.edu

***Abstract*— Traditional methods for gait analysis require stationary equipment, leading to limitations in mobility and real-world applicability. Wearable devices, particularly sensorized insoles, offer a promising solution for gait analysis during sports and dynamic activities. This study presents the development and evaluation of a custom-made sensorized insole for accurate estimation of Ground Reaction Force (GRF) and Center of Pressure (CoP) during human gait. The insole integrates pressure sensors and an accelerometer, coupled with Long Short-Term Memory (LSTM) models, to capture temporal dynamics in gait patterns. Data from eleven healthy adult volunteers were collected, pre-processed, and used for model training and validation. Results demonstrate the effectiveness of the sensorized insole, with improvements in prediction accuracy when combining pressure and acceleration data. The addition of accelerometer data to pressure data led to a reduction in the Normalized Root Mean Square Error (NRMSE) for the medio-lateral component of GRF from 18.4% to 16.7%. While challenges remain, particularly in modeling medio-lateral components of GRF, the study provides insights into potential future directions for optimizing sensorized insoles and improving model performance.**

Keywords—gait analysis; sensorized insole; wearable devices; long short-term memory; ground reaction force; center of pressure

I. Introduction

The analysis of human gait, a fundamental aspect of biomechanics studies, faces significant challenges in accurately capturing the dynamic interaction between the foot and the ground, known as Ground Reaction Force (GRF). GRF is three-dimensional and has three components, *i.e.*, antero-posterior, medio-lateral, and vertical [1]. Traditional methods, while providing valuable insights, are often constrained by the limitations of stationary equipment, such as the case of force plates, which restrict the natural mobility of participants and confine assessments to laboratory settings. Moreover, the complexity of accurately measuring multidimensional forces exerted during gait activities calls for innovative solutions that can offer both precision and flexibility.

In response to these challenges, the advent of wearable technology has opened new avenues for motion analysis, with sensorized insoles emerging as a promising tool to perform gait analysis during sports, in particular sports characterized by periodic movements such as race walking and running [2]. These devices, which are integrated with a variety of pressure sensors, provide insights into the complex distribution patterns of foot pressure and make it possible to analyze GRF in a manner that is not feasible with stationary force plates. However, the integration of these technologies into practical applications for gait analysis demands careful consideration of sensor resolution, data processing techniques, and the ability to estimate GRF components in real-world settings accurately.

Sensorized insoles employ diverse sensors, including force-sensitive resistors (FSRs), capacitive sensors, load cells, piezoelectric sensors, and optical fiber sensors. FSRs, in particular, are valued for their simplicity and cost-effectiveness, and change their resistance when the applied pressure changes, so the distribution of forces can be studied directly.

Given the complexity of estimating GRF and the center of pressure (CoP) during human gait, computer methods are required, and machine learning and neural networks are emerging as highly effective strategies in this field. These technologies provide an advanced approach for interpreting the intricate correlations and patterns seen in biomechanical data, allowing for more accurate analyses than is possible with conventional biomechanical techniques. In the literature, a wide range of models to estimate GRFs and CoP is explored, including machine learning methods like Linear Regression [3], Random Forests [4], Support Vector Machines, and neural

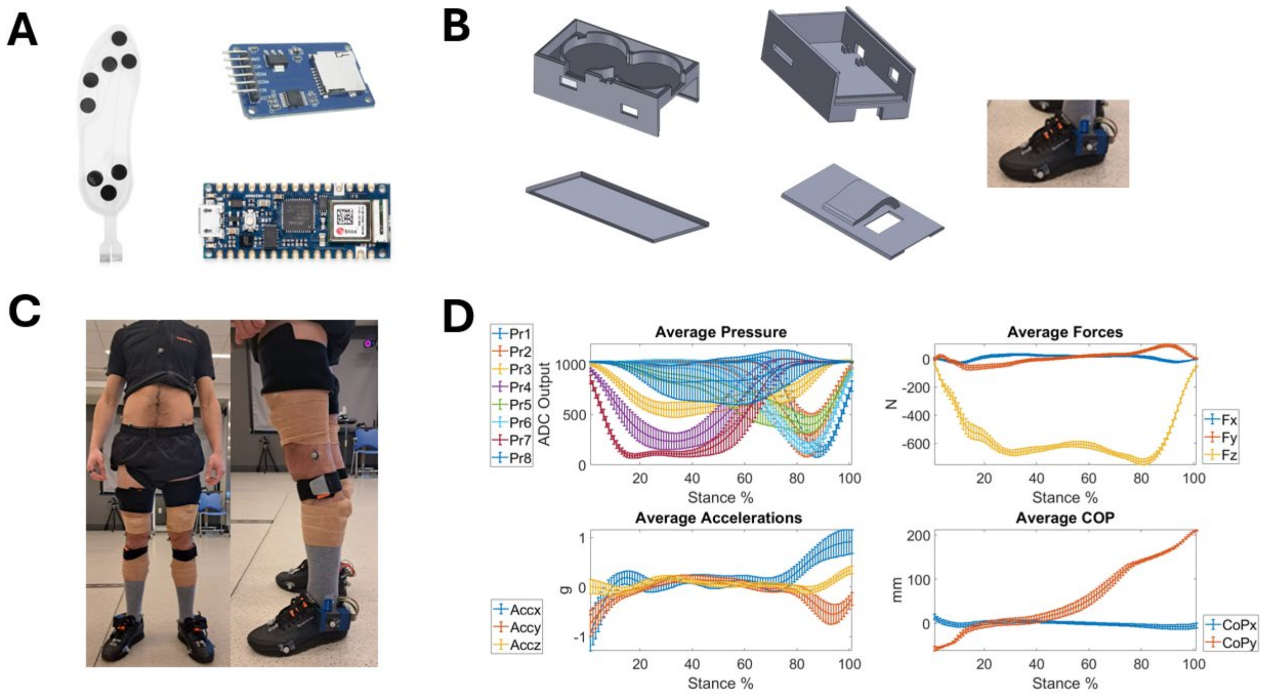

Fig. 1. A) Hardware components used in the study; B) Design of the 3D-printed case and how it is worn on the shoe; C) Experimental setup for data collection; D) Mean and standard deviation of data collected for one side of one participant.

networks like Convolutional Neural Networks, and Long Short-Term Memory (LSTM) [5], [6].

Despite such recent advancements, accurately estimating the mediolateral GRF component remains a significant challenge, largely due to the complex, multi-dimensional nature of lateral forces and their subtle manifestation in sensor data.

The aim of this work is to develop and evaluate a custom-made sensorized insole equipped with pressure sensors to accurately estimate GRF and the CoP during gait. Utilizing LSTM models, this work seeks to use the temporal aspects of walking patterns, offering an approach to understanding the dynamics of human gait.

II. Materials and Methods

A. *Hardware and firmware*

The design and realization of the sensorized insole for GRF and CoP estimation began with a set of hardware requirements to make the device wearable and suitable for collecting data in combination with other systems.

A thin film pressure sensor insole embedding 8 FSRs was chosen. A voltage divider configuration was designed as conditioning circuit. To read the pressure of these 8 sensors and to collect acceleration data to synchronize the insole with other devices, the microcontroller Arduino Nano 33 IoT [7] was chosen. This compact microcontroller board is equipped with over 8 analog inputs and an integrated accelerometer module (LSM6DS3), making it ideal for the task. The board is powered by two non-rechargeable lithium manganese dioxide coin batteries (CR3677X-HE1) with a nominal voltage of 6 V. All the data collected are stored locally on a SD module. The main hardware components used can be seen in Fig. 1A. The circuit of the device is encapsulated inside a custom-made 3D-printed case, connected to the insole by means of a D-sub connector. The case, illustrated in Fig. 1B, has a clip that allows the device to be inserted in the shoe without any additional straps, increasing its wearability.

The firmware was developed using the C programming language within the Arduino Integrated Development Environment. Its key function is to manage timing, enabling it to collect data at a frequency of 125 Hz. This sampling rate is achieved through the configuration of the microcontroller's TC3 timers [7] to trigger interrupt service routines at precise intervals. Data acquisition involved reading values from the 8 pressure sensors integrated into the insole, as well as the three-dimensional acceleration data from the onboard accelerometer. The firmware handled the analog-to-digital conversion of the pressure sensor signals and acceleration data, organizing these inputs into structured data packets for subsequent storage. A virtual circular memory mechanism was designed to temporarily store the data before the communication with the SD card is ready, enhancing the reliability of the gathered data and preventing sample loss. Moreover, the firmware incorporated features to enhance the device's usability. This included mechanisms for starting and stopping data collection via the user's interaction with the buttons on the device, as well as feedback to the user through LEDs indicating the device status and SD data transfer.

B. *Data collection and pre-processing*

Data were collected from eleven healthy adult volunteers. The experimental setup, shown in Fig. 1C, was designed to integrate a motion capture system with force plates, along with sensorized insoles fitted to each shoe. Participants were instructed to walk across the force plates, allowing for the simultaneous collection of data from the insoles and the force plates. In total, 867 gait cycles were collected across all participants enrolled in the study.

Fig. 1D shows all the data gathered from one representative participant. During data collection, pressure, and acceleration information were obtained from the insole,

TABLE I. COMPARISON BETWEEN NRMSE RESULTS OBTAINED IN THIS WORK AND RESULTS FROM THE LITERATURE (MEAN ± STD); 'PR' INDICATES DATA FROM THE PRESSURE SENSORS, WHILE 'PR&ACC' INDICATES DATA FROM THE PRESSURE SENSORS AND THE ACCELEROMETER.

NRMSE [%] obtained from sensorized insole					
Input	*GRF X*	*GRF Y*	*GRF Z*	*CoP X*	*CoP Y*
Pr	18.4 ± 9.1	7.3 ± 3.2	6.8 ± 2.3	24.0 ± 9.1	4.4 ± 1.6
Pr&Acc	16.7 ± 6.4	7.5 ± 2.7	6.9 ± 2.6	23.4 ± 10.0	5.1 ± 1.9
NRMSE [%] obtained in the literature					
Input	*GRF X*	*GRF Y*	*GRF Z*	*CoP X*	*CoP Y*
[5]	13.0 ± 4.9	6.3 ± 2.5	5.5 ± 2.3	n.a.	n.a.
[4]	13.7 ± 2.5	6.5 ± 1.5	7.7 ± 1.1	10.3 ± 4.3	5.4 ± 2.0

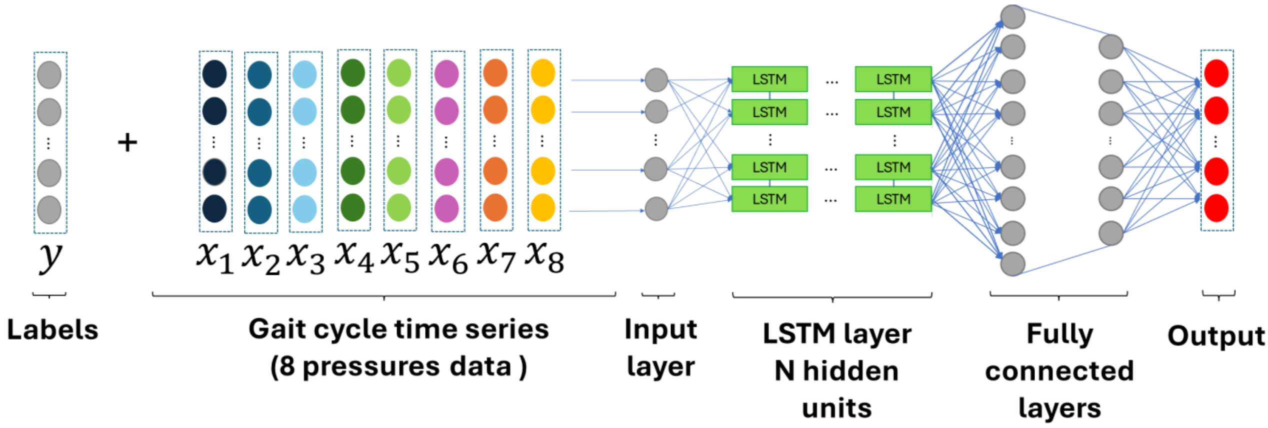

Fig. 2. Architecture of the neural network used to train the LSTM models (input: pressure data).

whereas GRFs and the CoP were measured by the force plates and derived from the motion capture system data, respectively. Data underwent pre-processing to fill gaps, label markers, and synchronize outputs across systems. Further, the data from all instruments were segmented into gait cycles and low pass filtered with a fourth-order Butterworth filter with a cutoff frequency of 6 Hz. To ensure the coherence and comparability of the collected gait data, pressure, GRFs, and CoP were aligned to a common reference system in the ankle joint center. This step was designed to eliminate biases associated with the walking direction and the laterality of the foot, as data were collected while participants walked in two different directions. Then, data were resampled at 101 points for each gait cycle. This uniformity is essential for the application of LSTM neural networks, which require consistent sequence lengths and reference systems. In the last step, pressure data were normalized against the minimum and the maximum average pressure per participant. Similarly, acceleration data were normalized against the minimum and maximum of the average values for each acceleration component per participant. GRFs were normalized by body weight and CoP data by the shoe size.

C. GRF estimation and training

Five separate LSTM models were developed, with each one dedicated to estimating a specific component of GRF ('GRF X', 'GRF Y', and 'GRF Z') and CoP ('CoP X', and 'CoP Y'). The neural network architecture used was the same for all five models. Each model was trained using two different sets of inputs. The first set comprised only the pressure data collected from the eight insole sensors; the architecture of the neural network used with this first set of inputs is shown in Fig. 2. The second set included both the pressure data and the acceleration data obtained from the microcontroller's built-in accelerometer; in this case, the architecture in Fig. 2 is only different in the input data (11 time-series, *i.e.*, eight series from pressure data and three series from accelerometer data). This strategy was deployed to understand the contribution of each type of data to the model's predictive accuracy.

To ensure the robustness and accuracy of each LSTM model, a training and validation process was employed, using Leave-One-Subject-Out (LOSO) cross-validation. This technique was chosen because of its ability to maximize the use of limited data, allowing each model to be trained on the entire dataset except for one participant's data used for validation. This approach is particularly beneficial given the dataset's size and helps to minimize overfitting, ensuring that the model's performance is dependable and generalizable across different participants.

Additionally, a Bayesian optimization technique was employed to find the optimal hyperparameters. This combination of LOSO cross-validation for the model validation and optimization of hyperparameter tuning provides a solid foundation for the development of accurate and dependable LSTM models to estimate GRFs and CoP.

III. RESULTS

Table 1 reports the aggregated results from the sensorized insole data (upper half) and a comparison with results from the scientific literature (lower half). In particular, the upper half of Table 1 shows the mean and the standard deviation of the Normalized Root Mean Square Error (NRMSE) percentage across various gait cycle components for two sets of input data: pressure data only ('Pr') and pressure data combined with acceleration data ('Pr&Acc'). The NRMSE values indicate the model's prediction accuracy, with lower percentages signifying closer alignment with actual measurements. From the reported data, it can be noted that the addition of acceleration data slightly improved the model accuracy in estimating the medio-lateral component of the GRF ('GRF X'), with a NRMSE of 16.7% compared to 18.4% obtained from pressure data alone. For the antero-posterior ('GRF Y') and vertical ('GRF Z') components of the GRF, pressure data alone demonstrated marginally better or comparable performances to models trained with pressure and accelerometer data together. The estimation of the CoP showed mixed results, with slight improvements in the antero-posterior component ('CoP X') when including acceleration data, while pressure data alone were more effective for the antero-posterior component ('CoP Y').

Two reference studies are chosen to compare these results with the literature, and their results are reported in the lower half of Table 1. The first reference reported is the study from Hajizadeh et al. [5], which uses the Tekscan insole, with 252 pressure data points combined with an LSTM model, and represents an upper limit for our work due to the inherent limitations of sensor density in our sensorized insole. Conversely, the second reference study by Oubre et al. [4] employs an insole with fewer sensors and no temporal modeling.

Fig. 3 displays the best model's predictions in each of the analyzed gait components for the different participants, compared to the actual measured values. In the cases of the vertical GRF for participant SS05 and the antero-posterior GRF for participant SS12, as well as the antero-posterior CoP for participant SS06, the model's prediction closely tracks the actual measurements, indicating that the device is capable of high accuracy. However, even though the late stance of the medio-lateral GRF of participant SS08 and the early stance of the medio-lateral CoP of participant SS12 follow closely the reference values, the GRF estimation in the early stance and the CoP estimation in the late stance demonstrate a greater distance from the actual measurements even in the best predictions.

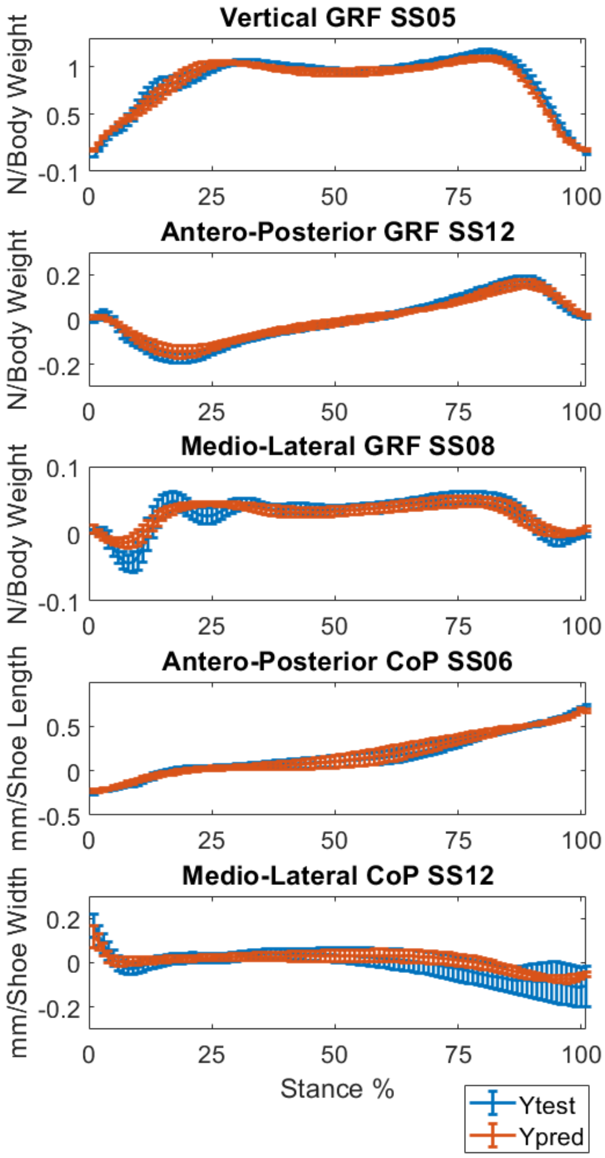

Fig. 3. Best predictions along each component (antero-posterior, medio-lateral, vertical GRF; antero-posterior, medio-lateral CoP).

IV. Discussion and Conclusion

The custom-made device constructed is a sensorized insole with eight pressure sensors. It incorporates an Arduino Nano 33 IoT microcontroller with a built-in accelerometer housed within a custom 3D-printed case for wearability and data collection efficiency.

The results in the upper half of Table 1 highlight the role of accelerometer data in enhancing prediction accuracy for medio-lateral gait components. However, while the inclusion of accelerometer data offers benefits in specific axes, pressure data alone remains highly effective for other components, underlining the complexity of modeling human gait dynamics. The approach described in this paper seeks to understand the trade-offs and balance between the richness of spatial data provided by multiple sensors and the computational complexity of time-series analysis required to process all these spatial data. It is of interest to determine if a low-resolution sensor array, when combined with an LSTM model, can provide sufficient data for accurate gait analysis, potentially offering a more cost-effective solution than higher-resolution commercial systems. The reported results show that while spatial resolution is a critical factor in sensor-based gait analysis, the integration of temporal data accounted for by the LSTM model holds significant promise, particularly for antero-posterior dynamics. Nevertheless, medio-lateral movement estimation remains a challenge.

The difficulty in modeling medio-lateral components, which can be visually appreciated in Fig. 3, could be due to the smaller magnitude of the range of lateral forces, which can be more easily affected by factors such as individual walking styles, sensor placement or even noise. Despite these challenges, the model captures the overall trend of the medio-lateral component, indicating its potential for further refinement.

This experimentation shows that LSTM models paired with low spatial resolution insoles are viable for gait analysis but also highlights areas needing further improvement. Future directions include improvements in data normalization, shifting from relative sensor activation levels to sensor characteristic curves for actual force measurements. This approach would enable the model to process direct force measurements instead of normalized pressure readings, potentially improving the model's interpretation of data by using physical quantities directly related to gait forces. Additionally, re-evaluating the pre-processing of acceleration data to include gravitational components that were removed for synchronization purposes could provide a fuller picture of gait biomechanics and improve model predictions. Future steps also include a hardware review, considering an insole with higher sensor density. By systematically assessing the different combinations that can be used and analyzing the impact on GRF and CoP estimations, the optimal sensor configuration for effective yet economical gait analysis can be investigated.

As the protocol presented in this study was performed by healthy volunteers who were walking without further requirements, future research works should be tailored for specific applications. For instance, a study during race walking or running could be used to assess the applicability of the presented solution during sports. On the other hand, in the case of medical applications, the model should be trained on data obtained from the clinical population on which the specific study is focused.

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