An off-line self-calibration method for resistive insole pressure sensors

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***Abstract*— Accurate and lightweight acquisition of human plantar pressure information such as vertical ground reaction force (vGRF) is crucial in applications such as clinical analysis and human-machine collaborative control. In recent years, resistive thin-film insole force sensors have become a representative solution, with advantages such as low cost, portability, and easy development. As the sensor is used for longer periods of time, more significant data drift is a problem that this insole sensor still needs to solve. In the subject experiment, the average root mean square error (RMSE) of the insole sensor measurements during the stance phase of the gait cycle which relative to the treadmill force platform measurements is approximately 44.7% of body weight, and the bimodal characteristics of vGRF in the stance phase were difficult to identify. To address this problem, this study demonstrates a low-cost offline self-calibration method for insole force sensors based on optimization, aiming to help users easily and efficiently improve the data accuracy of insole force sensors when walking on flat ground outdoors. The study built a wearable sensor system for experimental data collection and calibration method verification to autonomously collect the data required for the experiment. After the self-calibration method was implemented, the RMSE of the vGRF output by the insole force sensor during the support phase was approximately 10.2% (±0.6%) of the body weight, which was an average reduction of 77.2% in the error before calibration. The bimodal features corresponding to the vGRF could be significantly identified during walking. The results of this study show that this offline self-calibration method for insole force sensors can significantly improve the accuracy of plantar pressure information.**

I. INTRODUCTION

In recent years, in order to assist human activities, enhance human functions, and monitor human movement status, people's research on wearable devices such as lower limb exoskeletons and powered prostheses has gradually enriched. Real-time and accurate detection and perception of human motion information is the basis and key of wearable devices [1]–[3]. The foot is the only part of the body that comes into contact with the ground during daily walking, and its state contains rich information about human movement, posture, etc. Plantar pressure is the skin pressure on the foot, which is usually considered to be equal to the vertical ground reaction force. Its temporal distribution is an important indicator in sports training, clinical gait analysis, pathological foot diagnosis, and human-machine coupled collaborative control systems [4].

There are many methods that can help researchers or medical institutions obtain plantar pressure information of the human body in motion, such as the motion capture system [5] and the treadmill force measurement platform system [6], [7], which provide a simple and efficient method for exploring the basic biomechanical laws of the human walking process. However, these bulky systems can only be used in confined spaces and are usually expensive to build and maintain. In practical applications, when people need to wear assistive devices to help them exercise in complex outdoor environments, the motion sensing system requires extremely high portability and accuracy, so the pressure insole sensor solution provides a better trade-off [8], [9].

They usually use flexible materials such as silicone, fabric, composite materials, etc. and adopt different sensing principles (such as piezoresistive, capacitive, piezoelectric, etc.) to provide strong technical support for wearable applications. For example, the F-Scan system (Tekscan®, South Boston, MA, USA) [10]–[12] uses FSR resistive force sensors, and the Pedar system (Novel® GmbH, Munich, Germany) [13]–[15] uses embedded capacitive sensors. These commercial systems generally have good performance but are usually expensive. Many researchers have independently developed sensing insoles and tried to innovate in module structures and sensing materials. For example, Heng et al. developed a flexible pressure sensor for plane pressure detection, which improved the sensor performance and stability [16]. Lin et al. developed a plantar pressure measurement and analysis system based on a fabric pressure sensor array [17]. Zhang et al. developed a simple, low-cost, and highly integrated fabric-based plantar pressure measurement insole, whose principle mainly relies on the capacitive mechanism [18]. However, due to the light, thin and soft characteristics of these sensor units, they will produce unpredictable distortion and deformation on the contact surface. At the same time, they are affected by factors such as temperature and humidity, and cannot accurately measure the sensor response, resulting in nonlinear drift and repeatability problems [19]–[22].

There are many solutions to solve the problem of value drift of insole force sensors during use. Among them are methods based on static calibration, which applies a rated force to the sensor or tests it on a force plate, and then calibrates the data by translating, scaling, or adding a time factor [22], [23]. There are also calibration platforms like the Pedar system, where the calibration software and hardware are integrated into one system and the insole is placed

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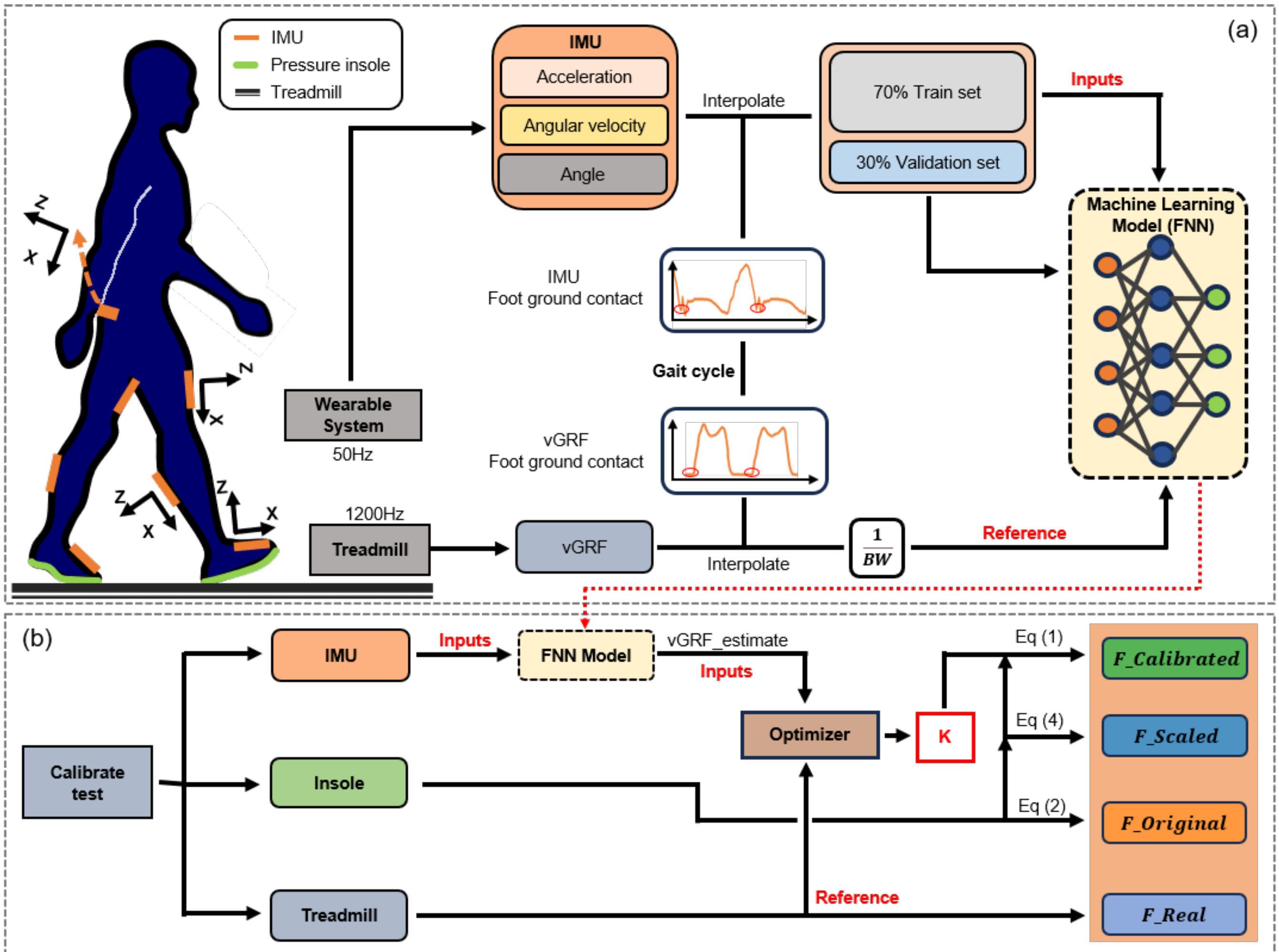

Fig. 1. Wearable data acquisition & offline calibration system construction. (a) The heel strike event is determined and the data is aligned through the front and rear calf angular velocity of the IMU and the force measuring treadmill vGRF. All data are interpolated to 100 frames, and the subject's weight (including equipment) is used to standardize the pressure information. The IMU is used as input and the treadmill vGRF is used as reference to train the neural network prediction model. (b) Walking calibration experiment in progress. (c) During calibration, the IMU data of the user's gait cycle support phase is interpolated and input into the prediction model. The output $vGRF_estimate$ will be used as the calibration standard value, and the coefficient matrix K is the optimization target.

in the device for calibration [13]. The above methods can accurately calibrate the insole force sensor, but they either rely on external platforms and are expensive, or are not portable and have complicated processes.

Therefore, in order to improve the accuracy of the insole pressure sensor while taking into account low cost, real-time performance and portability, we designed a self-calibration method. This method aims to use sensors with a limited number and cost to help users easily calibrate insoles force sensors in outdoor scenarios. The study built a wearable data acquisition system. The data was based on resistive insole force sensors and inertial sensor units. The acceleration of the lower limbs and the distributed force of the sole of the foot when the human body walks were obtained, and a data set was created for experiments and tests. The walking experiment was conducted on a treadmill force platform, and the vertical ground reaction force (vGRF) output by the treadmill was used as the true value for model training and method verification.

II. Methods

A. Offline prediction of vertical ground reaction forces

The core of the first part of this research is to build a high-precision estimation model to accurately estimate the lower limb motion information of the subject in an offline state. This study uses a supervised learning framework to train a machine learning model based on self-collected human motion data. To ensure same amount of information is provided to the network model, all gait cycle stance phase data are interpolated to contain 100 timestamps. Referring to the lightweight network design paradigm of [24] prediction task, a two-layer feedforward neural network (FNN) is constructed. The hidden layer contains 10 neurons, and the Sigmoid activation function is used for nonlinear feature mapping; the output layer consists of 100 linear neurons, which are used to directly regress the vGRF time series

$(F_1, F_2, ...F_{100})$, covering the complete gait cycle.

To simplify the model, we assume that the left-right movements of all subjects are completely symmetrical. The right foot support phase with stable walking state in the experiment is selected. The model input include IMU signals of the waist, right thigh, calf, and instep, and the right foot treadmill the baseline of the vGRF measurement. The subject's body weight (BW) is used to standardize the treadmill vGRF to improve model training efficiency.

The experimental data contains 1361 independent support phase samples, of which 953 are randomly selected as training sets and validation sets (covering different subjects and different walking speeds to enhance the generalization ability of the model), and the remaining 408 are used for independent testing. RMSE is used as the loss function, and the Adam optimizer is used for parameter update.

B. Nonlinear timing matrix calibration method

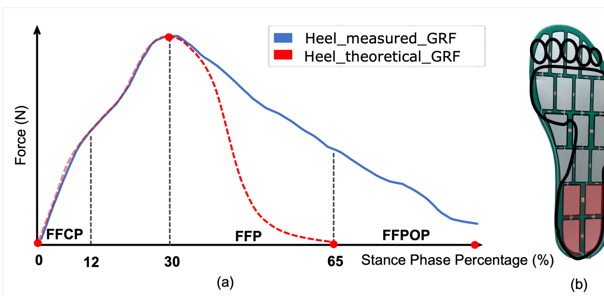

Fig. 2. Disadvantages of thin-film resistive sensors in insole applications. (a) The performance of the sum of vGRF measured in the heel area during uniform walking during the gait cycle. (b) Schematic diagram of the insole force sensor used in this experiment, with the red area defined as the heel area.

As shown in Fig.2(a), the resistive pressure sensor will produce significant residual force output when the pressure is quickly removed, causing data drift and nonlinear characteristics in the insole module. Based on the study of gait cycle speed [24], at the walking speed selected in this experiment, forefoot contact phases (FFCP) are approximately 0%-12% of the stance phase, foot flat phases (FFP) are approximately 12%-65% of the stance phase, and forefoot push-off phases (FFPOP) are approximately 65%-100% of the stance phase. The area marked in red in Fig.2(b) is the heel area, which should be completely off the ground at the beginning of FFPOP. We assume that the sum of the sensor measurements after the heel area leaves the ground should be 0, so the curve of the true value of vGRF in this area in the full support phase can be estimated by the red dotted line in Fig. 2(a). However, due to the continuous output of residual force by the sensor, the vGRF in the heel area increased by an average of 30.6% between the peak value (about 30% of the support phase) and the end of gait, and increased by 21.4% in the complete gait cycle. This characteristic causes the insole sensor to have severe nonlinear drift, and the output vGRF is difficult to identify the typical double-peak characteristics.

To solve the above problems, this study proposes an optimization-based calibration method, which predicts $vGRF\_estimate$ through a trained neural network model and calculates the time-series-related coefficient matrix offline to replace the traditional time-invariant calibration method. Fig. 1(c) shows the calibration process.

$$\mathbf{P}_{\text{calibrated}} = \mathbf{P}_{\text{original}} \circ \mathbf{K} \tag{1}$$

$$\text{where} \quad \mathbf{P}_{\text{ori}} = \begin{pmatrix} \mathbf{p}_1^\top \\ \mathbf{p}_2^\top \\ \vdots \\ \mathbf{p}_{100}^\top \end{pmatrix}_{100\times 18}, \mathbf{K} = \begin{pmatrix} \mathbf{k}_1^\top \\ \mathbf{k}_2^\top \\ \vdots \\ \mathbf{k}_{100}^\top \end{pmatrix}_{100\times 18}$$

Specifically, for gait cycles of different speeds, all the time from heel touching the ground to toe leaving the ground is interpolated to 100 timestamps. Assuming that the true value of vGRF in each frame can be represented by the linear product of 18 pressure sensors on the sole of the foot and the coefficient vector, then for the stance phase of the complete gait cycle, the relationship between the actual measured value and the true value can be expressed by the formula 1. This method introduces the gait timing characteristics.

$$\mathbf{F}_{\text{calibrated}}(i) = \sum_{j=1}^{18} \mathbf{P}_{\text{calibrated}}(i, j), \quad i = 1, 2, \ldots, 100 \tag{2}$$

In order to obtain a matrix that can minimize the global error of vGRF in all gait cycles, the Adam optimizer is used for optimization, and the loss function is defined by RMSE. The optimized two-dimensional coefficient matrix K provides dynamic calibration parameters for all pressure sensors at different percentages of the support phase. Finally, the original data of the insole sensor and the matrix K are linearly multiplied 1 and then summed 2 to obtain the calibrated vertical ground reaction force ($F_{Calibrated}$).

III. Experiments

A total of 3 subjects (age: 21.5 ± 1.5 years, height: 1.79 ± 0.06 m; weight: 70 ± 3.5 kg) participated in the experiment. All participants were free of any musculoskeletal injuries and neurological diseases that might affect their performance in the experimental tasks. The project was approved by the Institutional Review Board of Southern University of Science and Technology, and all participants provided written informed consent before participating in the experimental procedures. The experiment was conducted in accordance with relevant guidelines and regulations. The wearable data acquisition device used in the experiment is shown in Fig. 1. A total of seven inertial measurement units (IMUs) with ± 16g (accelerometer), ± 4000 degrees/second (gyroscope), Y axis ± 90 degrees, X, Z axis ± 180 degrees (angiometer) were arranged on the waist (lower back), the front of the left and right thighs, the back of the calf, and the instep (shoe upper) of the body, with a sampling frequency of 50Hz. This study used an insole force sensing module consisting of 18 resistive force sensors. The range of a single sensor was 0-500N. The module was installed under the initial insole of the experimental shoe, and the sampling frequency was 50Hz. All walking experiments were conducted on a treadmill. The treadmill force platform collected the ground reaction force (vGRF) of the subjects' feet when they walked, with a sampling frequency of 1200Hz. In order to eliminate the influence of different shoe shapes, materials, tightness, and insole sensor sizes on the experimental results, all subjects wore the same shoes, and the insole sensors and shoe sizes were both European size 42.

The experiment is divided into two parts. The first part is used to collect the data set for training the neural network model. The subjects wear the sensor system and conduct a walking experiment on the treadmill. The participants are asked to walk on the treadmill force platform at four speeds of 0.9, 1.0, 1.1, and 1.2 (m/s) for about 2 minutes. Before the walking experiment, the subjects stand on both feet and left and right feet for a period of time to standardize the initial values of the treadmill force platform and the insole force module, and to estimate the extrusion pressure generated inside the shoe and the drift of the insole when it is unloaded. The data set excludes three gait cycles before and after reaching a stable walking state to improve the stability of the data. The second part of the experiment is used to test the calibration performance. The subjects select a comfortable step frequency and walk on the treadmill at a uniform and non-uniform speed for a period of time, with a speed between 0.9-1.2m/s. The gait cycle of 15 seconds was randomly selected to calculate and optimize the calibration coefficient matrix. Fig. 1 (b) shows the calibration experiment conducted on the treadmill.

The acceleration of the IMU in the x direction at the shank is used for data synchronization and segmentation of the support phase [25]. The treadmill vGRF is detected with a 15N threshold. The heel-strike is considered as the start of the stance phase, and the toe-off is considered as the end of the stance phase. The method of determining gait events through human kinematic parameters has been verified [26], [27]. In the swing phase, the value of the vGRF greater than zero is considered to be noise, so only the support phase data of the gait cycle is retained.

IV. Results

A. Evaluation of the prediction effect of feedforward neural network

After completing the prediction model construction and training, we use the test set data to evaluate the model performance. As shown in Fig.3, several gait cycles that can represent the average situation are selected. The blue line corresponds to the average prediction result after smoothing, and the orange area shows the range of vGRF prediction values. Model performance is evaluated by the root mean square error. Fig. 3(b) shows the RMSE mean and distribution of the prediction results in one of the subjects. The average RMSE among all subjects is 4.7%, and the standard deviation is 1.5%. The above results show that the neural network prediction model constructed in this experiment can be used in the insole force sensor calibration process.

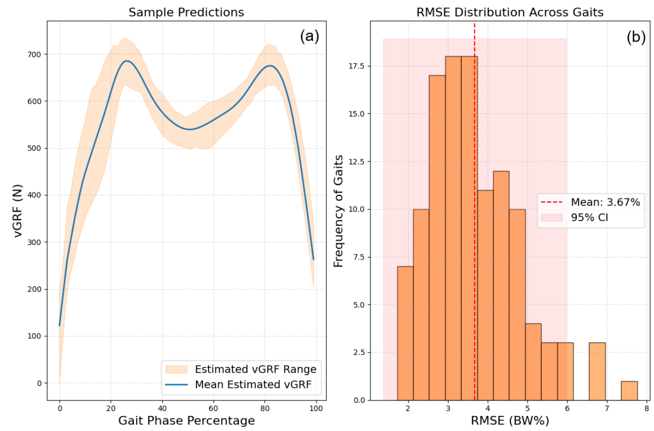

Fig. 3. Prediction performance of the FNN model for vGRF. (a) The blue line corresponds to the average prediction result after smoothing, and the light-colored range shows the prediction value range. (b) The distribution of the RMSE of the prediction results and its 95% confidence interval.

B. Evaluation of nonlinear timing matrix calibration method

In order to more intuitively demonstrate the performance of the calibration method, a common calibration method is introduced as a comparison group, that is, directly using the translation and scaling method to deal with the insole sensor data drift. The formula is:

$$k = \frac{(W - T) \cdot g}{F_{\max} - F_{\min}} \tag{3}$$

$$F_{\text{scaled}} = (F_{\text{raw}} - F_{\min}) \cdot k + T \tag{4}$$

Where k is the scaling factor, W is the subject's weight, T is the sensor threshold monitoring 15N, and the gravity acceleration g is 9.8m/s^2.

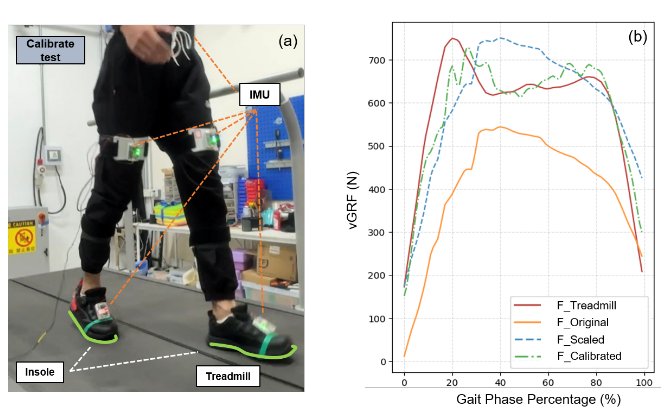

Fig. 4. Insole force sensor calibration experiment. (a) shows the subject wearing the sensor system and performing a walking experiment on a treadmill. (b) shows a gait cycle that can represent the average state and the vGRF curves before and after calibration using different methods.

The measured values of the treadmill are taken as the true values. The walking data of the subjects' self-selected speed are used as input. As shown in Fig. 4(b), a gait cycle that can represent the average situation is selected, where the red

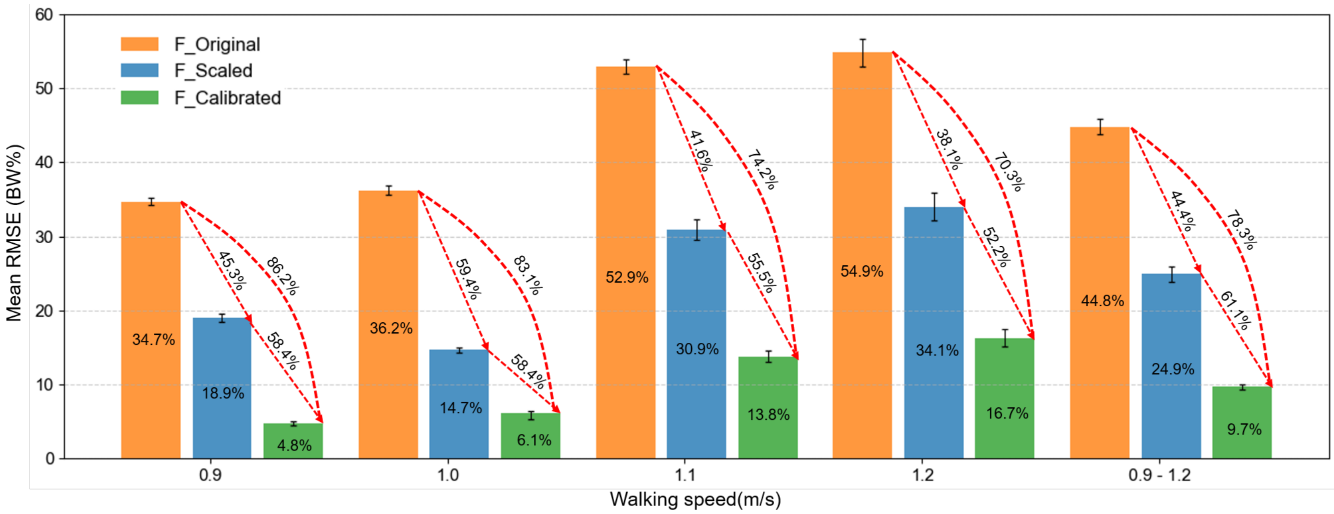

Fig. 5. The verification of optimized calibration effect and the RMSE of different calibration methods when walking at different speeds.

line represents the vGRF recorded by the treadmill force platform, the yellow line represents the unprocessed vGRF data of the insole force sensor, the blue line shows the vGRF calibration curve that has only been translated and scaled, and the green line is the vGRF curve after processing using the calibration matrix.

As shown in Fig. 5, the calibration method we proposed can reduce the RMSE (BW%) to about 10.2% on average at different walking speeds, which is about 58.7% higher than the average RMSE of 24.7% of the scaling and translation method. At the same time, it can be seen that this method has high repeatability between different gait cycles and high robustness at different walking speeds.

Considering that it is difficult for subjects to accurately control walking speed, frequency and stability in actual situations, we also test under variable speed walking conditions. During the test, the treadmill speed is controlled to change gradually between 0.9-1.2 m/s, and the subjects walked along a straight line at a comfortable step frequency. All gait cycles are used to calculate the calibration matrix. In this case, as shown in Fig. 5, the average RMSE after calibration in this speed change case is 9.7%, which is close to the average result of 10.2% in the same speed calibration experiment. Therefore, the proposed method has high repeatability between different gait cycles and high robustness at different walking speeds.

V. Discussion and Conclusion

This study proposes an offline self-calibration method for low-cost resistive insole pressure sensors, which helps the module output accurate vertical ground reaction force using limited sensors and a simple calibration process. The experimental results show that after calibration, the RMSE of the vGRF in the support phase is reduced to 6.6% (±3.3%) of the body weight, which is 85.2% lower than the average error before calibration and about 75.3% lower than the average error of the scaling and translation calibration method. The double-peak characteristics of vGRF can be significantly identified.

The innovation of this study lies in: (1) the motion data is dynamically associated with the drift characteristics of the insole sensor to achieve dynamic coefficient optimization; (2) a lightweight calibration process is proposed to reduce the system deployment cost and reduce the dependence on external equipment.

This research is expected to promote universal health monitoring and exercise optimization, realize real-time and accurate monitoring of plantar pressure distribution, provide gait assessment and fall risk warning for the elderly, diabetic patients, etc. lower the threshold for the use of home health monitoring equipment, promote hospitals or rehabilitation institutions to remotely monitor patients' daily conditions, and improve the utilization rate of medical resources.

As for the research on human augmentation equipment, most of the equipment is equipped with data monitoring modules such as IMU, so it is possible to improve the real-time performance of the system for plantar interaction force information at a limited cost, helping to achieve accurate human-machine compliant control. Reduce the development cost of wearable robot systems and promote the commercial application of new consumer health products (such as power-assisted shoes and lower limb exoskeletons).

The current study still has certain limitations. The data only come from healthy subjects with similar physical conditions. Due to the limitations of test conditions, the exercise scenes are limited, and the tests in different situations are simulated on a treadmill. Future work will expand the verification of feasibility and effectiveness under variable speed motion (such as slower walking (< 0.9m/s), faster walking (>1.2m/s), running), curved walking, and climbing stairs.

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