A Shoe-Integrated Sensor System for Long-Term Center of Pressure Evaluation

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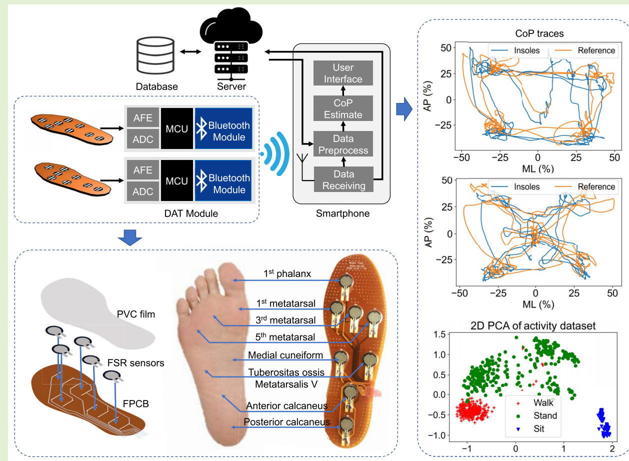
***Abstract*—In clinical, the center of pressure (CoP) is commonly used for accessing the stability of a person's postural control, which is highly associated with various neurological diseases and movement disorders such as Alzheimer's disease, Parkinson's disease, chronic ankle instability. Such a disease usually has a long development or rehabilitation process which requires long-term CoP monitoring. The current CoP evaluation process does not meet the requirement, as it is often complicated and expensive through either the lab-based equipment or the clinical evaluation procedure. Different wearable sensor-based systems with less cost and restrictions have emerged, but their way of CoP calculation requires deliberate calibration of the positions of their sensors, which are not feasible in daily CoP monitoring. In this study, we developed a long-term CoP monitoring system in a smart-shoe form. First, a thin and flexible smart insole with optimal sensor locations was designed to be compact and energy sufficient for a whole-day usage. Then, a user-friendly app on the smartphone with a cloud-based data managing system was developed for applications in both clinical and home environments. Additionally, a simplified CoP estimation model was created without the need for calibration. Lastly, a machine learning-based human activity recognition method was incorporated to make the CoP detection process more automatic. Through a thorough validation test with the clinical level lab equipment, our system can generate the CoP measurements with high accuracy.**



***Index Terms*—Activity recognition, center of pressure (CoP), plantar pressure, smart insole, static postural control.**

I. Introduction

POSTURAL control that can be characterized by maintaining, achieving, and restoring equilibrium against gravity during stance or locomotion, is considered as one of the most fundamental motor skills in the lifetime [1]. Insufficient postural control, which often results in larger amounts of postural sway, is highly associated with movement disorders like chronic ankle instability [2], low athletic performance [3], and many neurocognitive diseases, such as Alzheimer's disease, Parkinson's disease [4]. The center of pressure (CoP, global ground reaction force vector) displacement, which accommodates the sway of the body, is commonly used to assess these diseases [2], [3]. As such a disease usually has a long development and rehabilitation process, long-term CoP monitoring is often required, which is also helpful in improving early diagnosis [4]. Effective daily CoP monitoring can be used in various clinical applications as well, such as fall risk estimation, assessment of recovery, test and train postural control and sway, and general gait analysis [5], [6]. The gold standard for CoP measurement is a validated force platform, whose accuracy and reliability was proofed by tests and statistical analyses [7]. However, the force platform-based CoP measurement has severe limitations such as restricted laboratory settings, required operations of an experienced therapist, and expensive devices. Therefore,

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such a method cannot satisfy an increasing demand for daily CoP monitoring and training both in medical and community environments.

With the development of wearable sensor systems, the foot pressure measuring insoles with comfortable and realistic settings have become a promising alternative for CoP measurement. With much lower cost and less restriction by the environment, it is more suitable for outdoor CoP monitoring. To date, a variety of wearable insoles has been investigated. Tan *et al.* developed a pair of low-cost insoles whose accuracy was proved by the standard Kistler force plate [8]. However, the insoles need to wire to the computer during working, which might affect the user's normal gait. Later, a wearable smart insole system that consists of an array of sensors and has wireless communications with the smartphone was presented by Lin *et al.* [9], but the accuracy was not validated. By utilizing the Force Sensing Resistive (FSR) sensors and flexible printed circuit board, different forms of flexible insole-based systems have been developed with high comfort [10]–[13]. In all the previous systems, the direct way of calculating CoP displacement, i.e., averaging the ground reaction forces over the sensor locations, was commonly employed. Such a method is not feasible in the daily CoP monitoring, as the sensor locations of each user are unknown unless through careful calibration of the foot positions. Also, the sensor locations in these systems were all set differently without justifications, which might also affect the accuracy of CoP measuring.

In this paper, we developed a shoe-integrated system for long-term CoP monitoring. First, a thin and flexible smart insole with optimal sensor locations was designed, which can be assembled into various kinds of shoes without affecting the user's normal gait. The overall system hardware is compact and energy sufficient for a whole-day usage. A user-friendly app on the smartphone with a cloud-based data managing system was then developed for applications in both clinical and home environments. Additionally, a simplified CoP estimation model was created without the need for sensor location calibrations. Combining with a machine learning-based human activity recognition method, the overall CoP detection process was made to be simple and automatic in both home and clinical environments. Through a thorough validation test with the clinical level lab equipment, our system can generate the CoP measurements with high accuracy.

II. System Design

A. System Overview

The overall structure of the system consists of three parts, i.e., the system hardware part, the CoP analysis software on the smartphone, and the cloud-based user database, the relationships among which are illustrated in Fig. 1. Whenever a user initiates a CoP test, the hardware part first detects the plantar pressure on both feet and transmits the data wirelessly to the CoP analysis software in real-time. Then the program synchronizes the data from both feet and extracts and saves the valid plantar pressure data locally. After a CoP test is finished, all the pressure changes are converted into the CoP coordinates and the analysis results are generated and presented through a user-friendly user interface (UI). At the same time, the software also contacts the cloud server and synchronizes the user data with its user database. Later, the users and their doctors can retrieve all their previous test data and analyze the results again.

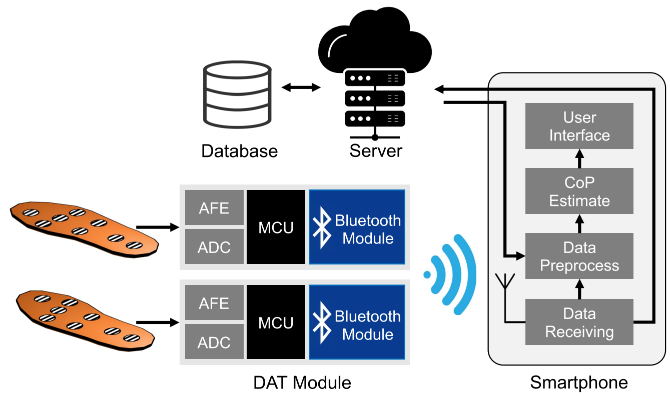

Fig. 1. The illustration of overall system architecture.

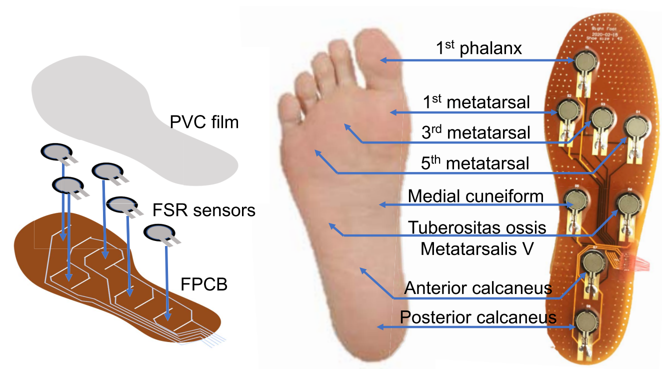

Fig. 2. The structure of the pressure detection insole and the definition of the sensor locations.

B. Hardware Design

The system hardware comprises two individual plantar pressure insoles and their corresponding data acquisition and transmission modules (DAT), which can efficiently sample and transmit the plantar pressure data to the host computer, i.e., the smartphone. To satisfy the long-term daily monitoring, it is required to achieve a low power consumption and a compact size for both the insoles and DAT modules, so that the user's natural gait is not distorted.

The pressure detecting insole was designed to be a sandwich structure, as presented in Fig. 2. First, a flexible printed circuit board (FPCB) was fabricated to form the insole substrate and implement the circuits that set the sensor locations and connect them with the DAT module. The pressure sensors were then integrated into the FPCB by welding and sticking one side firmly to the FPCB. For improving the overall reliability, a thin polyvinyl chloride (PVC) film is sealed on the very top to protect both the sensors and circuits without absorbing the forces applied on the sensors.

The FSR sensors (Model 402, Interlink Electronics, Westlake, USA) were used as the sensing units, as they were proved to be sufficient for plantar pressure measurement applications in both static and dynamic loading [11], [12]. Since CoP

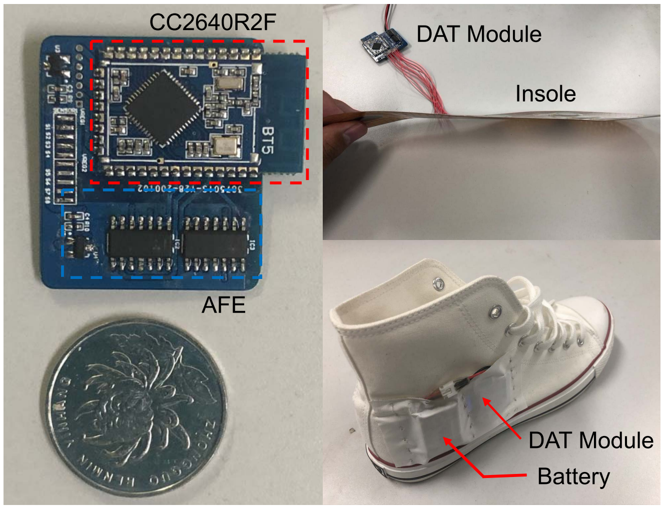

Fig. 3. The display of the DAT module, the insole, and the overall hardware in a shoe.

displacement is the average of the ground reaction forces over the feet, the most accurate way of measuring CoP is to sample the plantar pressure at every point under the feet evenly. However, such a method does not apply to a wearable system, as it is hard to maintain a low energy consumption and a high data sampling rate with so many sampling points through wireless transmissions. Claverie *et al.* showed that sensors with a carefully designed discrete layout, i.e., the main stress locations, can still achieve similar accuracy as those of many more sensors [14]. Therefore, to minimize the power consumption while maintaining high accuracy, we use a similar setup of 8 sensors with a more even distribution so that each sensor has the same weight in the CoP calculation. The actual locations are the first phalanx, first metatarsal, third metatarsal, fifth metatarsal, medial cuneiform, tuberositas ossis metatarsalis V, anterior calcaneus, and posterior calcaneus (see Fig. 2), where the sensor at medial cuneiform was set for users who have flat feet.

The design of the DAT module has a compact size of 35 mm by 35 mm shown in Fig. 3. It is composed of the analog front-end (AFE), analog to digital converter (ADC), microprocessor, and Bluetooth module, of which the last three items are packed in a single CC2540R2f chip made by Texas instrument inc, Texas, USA. In AFE, each FSR sensor is tied with a measuring resistor as a voltage divider to perform the force-to-voltage conversion. The measuring resistor was selected to maximize the desired force sensitivity range and to limit the current. The voltage divider is followed by an emitter follower and an amplifier implemented by a general operational amplifier chip (LMV324, Texas instrument inc, Texas) and connected to an ADC with a sampling rate of 100 Hz. The average working current is around 20 mA, and a 500 mAh battery was selected as the power supply, which can satisfy a whole day's usage.

With a thin and flexible insole and a compact DAT module, the overall hardware can be easily assembled into a regular shoe, as illustrated in Fig. 3. By adjusting the FPCB design according to the shoe sizes and sensor locations, our hardware can be well fitted into a variety of shoes, e.g., sizes from

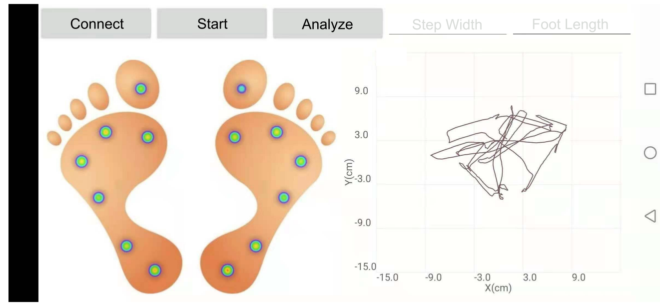

Fig. 4. The user interface on a smartphone where the real-time plantar pressure and CoP displacement are presented.

UK4 to UK10. As tested by the users with different kinds of shoes, the overall system is comfortable and reliable and is qualified for daily plantar pressure sensing.

C. Software Design

The software on the smartphone contains four stacked layers (see Fig. 1), of which the implementation uses multithreading for the sake of real-time CoP computing. After a user initiates a connect request in the UI console (see Fig. 4), the first layer searches the devices and initiates two individual Bluetooth connections with both two insoles. After the user starts a CoP test through the UI, it receives both feet' plantar pressure data simultaneously over the Bluetooth Serial Port Profile (BSPP). Due to the instability of wireless communication and two feet asynchronous data transmissions, the first layer needs to synchronize the incoming sensor data before forwarding it to the next layer. It regulates the data by applying the sampling rate of 100 Hz and minimizing the time differences of certain walking events between two feet, e.g., walking start and stop.

The second layer performs the data preprocessing. First, it examines the packet loss rates of all data by counting up the timestamps in each data frame. If any channel encounters a significant data loss, e.g., the packet loss rate is higher than 5% due to a weak connection, it dropped out all the data received during this period considering they are invalid. Otherwise, any small amount of missing data of this period are recovered through a polynomial interpolation. Then, the sensor data in each channel are de-noised through a median filter and converted into pressures through a voltage-to-pressure conversion. Such a conversion can be calculated by the circuit structure, i.e., the measuring resistor and the amplifier in the DAT module, and the measured curve of the force changing with the resistance for FSR sensors, provided by the sensor manufacturer. We use the least square polynomial curve fitting method to approximate this curve. The data preprocessing in each sensor channel is assigned to a single thread to increase efficiency.

The CoP estimation layer uses the converted pressure data from each sensor to calculate the CoP coordinates through a simplified CoP calculation model, which is discussed in section III. It also contains the CoP analysis algorithms to derive the commonly used parameters of the CoP test, e.g., the average CoP center and CoP variation in the AP and ML directions. Eventually, the instantaneous plantar pressure

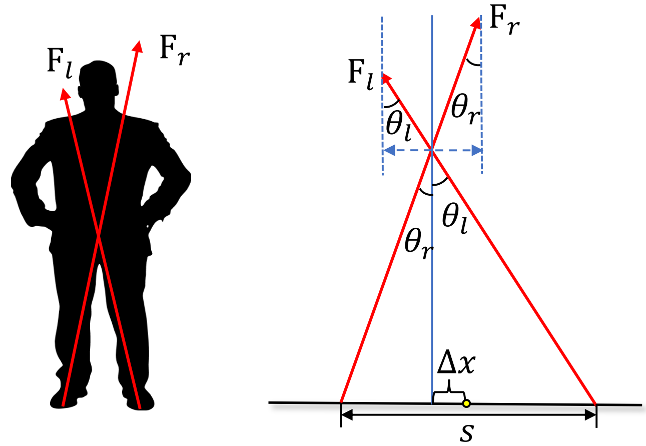

Fig. 5. The simplified model of calculating the static CoP location in ML direction.

and CoP trace results are presented to the user on the UI layer in real-time (see Fig. 4), where users can also control the functionality of the whole system.

After a user initiates and finishes a CoP test, all the synchronized plantar pressure data are recorded in a single file. Through the data management system, the users can upload and store the test file into the user database on the cloud server via the TCP/IP connections. The cloud server maintains a file directory for each user, which contains all the test files, and a SQL database, which contains user and test information linked to each file. Later, the users and their doctors can retrieve all the previous test data and perform a long-term CoP evaluation, which is useful for evaluating their therapies and rehabilitation.

III. Automatic CoP Estimation

A. Static CoP

The static CoP test is commonly used in the postural sway evaluation during still upright stance, which is highly associated with the risk of falls in the elderly [3], [15]. In the test, static double or single-limb standing balance tasks with opened or closed eyes are often employed as valid conditions to examine the postural sway. The general way of calculating CoP in anteroposterior (AP) and mediolateral (ML) directions is through the following equation [11]:

$$(X_{CoP}, Y_{Cop}) = \frac{\sum_{i=1} F_i X_i}{\sum_{i=1} F_i}, \quad \frac{\sum_{i=1} F_i Y_i}{\sum_{i=1} F_i}, \tag{1}$$

where X_{CoP} and Y_{Cop} are the instantaneous CoP positions in the direction of ML and AP, respectively. F_i is the force detected by the sensor i, whose coordinates of its center are X_i and Y_i. Although the relative location of each sensor in an insole is fixed, a person may have a different distance and an angle between the feet during the daily activities. Therefore, the absolute coordinates X_i and Y_i are difficult to be derived and may change at each test, which makes this method inapplicable in daily CoP monitoring.

In this study, we developed a simplified model of the relative CoP positions, which does not require absolute coordinates. First, we present the CoP calculation in the ML direction, whose model is shown in Fig. 5. Suppose the total forces on the left and right feet are F_l and F_r, and the angles between them and vertical are θ_l and θ_r, respectively. The distance between the two feet is s, and the middle point of s is defined as the origin. To keep the balance of the body, the CoP position needs to be aligned with the center of the body, whose lateral distance from the origin is Δx. From the equilibrium, we have the following equation,

$$F_l \cdot \sin\theta_l = F_r \cdot \sin\theta_r. \tag{2}$$

Also from Fig. 5, we can have the following relationship,

$$\frac{\frac{s}{2} + \Delta x}{\frac{s}{2} - \Delta x} = \frac{\tan\theta_l}{\tan\theta_r}. \tag{3}$$

The relative CoP change in ML direction $\tilde{X}_{CoP}$ can be derived as

$$\tilde{X}_{CoP} = \frac{\Delta x}{s} = \frac{1}{2} \cdot \frac{\tan\theta_l - \tan\theta_r}{\tan\theta_l + \tan\theta_r}. \tag{4}$$

In reality, θ_l and θ_r are usually very small, and the following approximations can be made.

$$\begin{cases} \theta_l \approx \tan\theta_l \approx \sin\theta_l \\ \theta_r \approx \tan\theta_r \approx \sin\theta_r. \end{cases} \tag{5}$$

From (2), (4), and (5), the $\tilde{X}_{CoP}$ can be derived as

$$\tilde{X}_{CoP} \approx \frac{1}{2} \cdot \frac{F_r - F_l}{F_r + F_l}. \tag{6}$$

The same model can be applied to the CoP position in the AP direction but with total forces on the front and back part of the feet, i.e., F_f and F_b, as

$$\tilde{Y}_{CoP} \approx \frac{1}{2} \cdot \frac{F_f - F_b}{F_f + F_b}. \tag{7}$$

B. Dynamic CoP

The dynamic CoP estimation is the measurement of the CoP changing on each foot during walking, which provides considerable insight into dynamic foot function [13]. In this case, each foot is evaluated separately, and the positions of the sensors on each foot are fixed. Therefore, (1) can be applied to generate the instantaneous CoP positions, which has been verified by many papers [9], [11]–[13]. Through this method, a typical result derived by our system is illustrated in Fig. 6. It shows that the CoP location moves from the heel to the forefoot and eventually to the toe during a normal walking cycle.

C. Activity Recognition

With the development of the wearable sensor-based system, various state-of-the-art techniques have been proposed in human activity recognition to continuously monitor human behaviors in various smart home environments [16]. In a long-term CoP monitoring process, such an activity recognition method is necessary so that different CoP estimation models can be applied automatically. We classified the human activities into standing, walking, and siting, corresponding to the static, dynamic, and no CoP estimation models accordingly. Before training a machine learning model, the plantar pressure

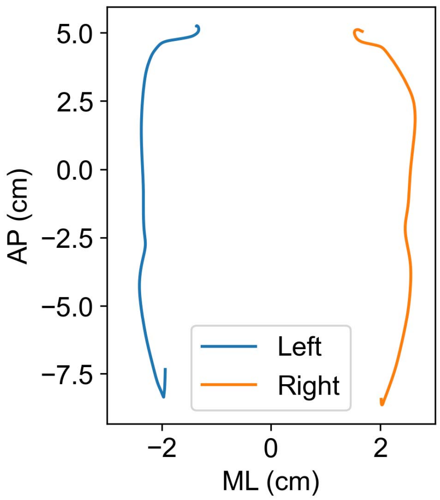

Fig. 6. The dynamic CoP traces detected during walking.

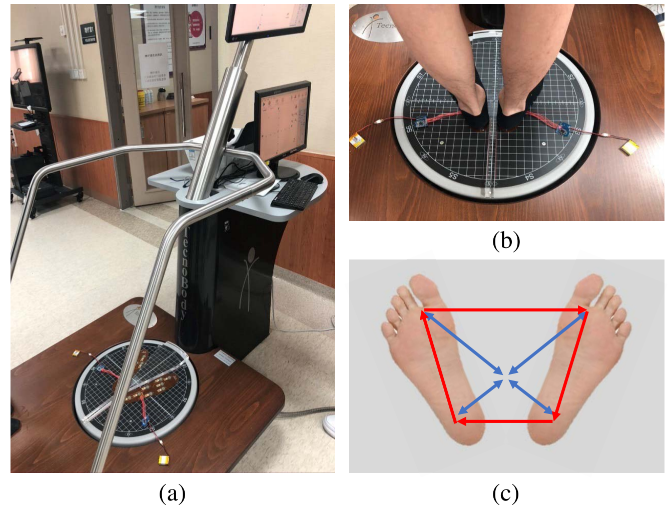

Fig. 7. The (a) equipment, (b) setup, and (c) procedures of the CoP validation test.

data of all 16 sensors were collected for all three activities. Then a 2-second window was applied to segment the data into samples. In each sample, the mean and standard deviation of all the pressure data were extracted as the input features, and then a total of 32 features was passed to a multi-class support vector machine (SVM) with Radial Basis Function (RBF) kernel as the classifier. It should be noted that all the features were normalized before being employed in the classification stage and the parameters of the kernel were optimized.

IV. Experimental Protocols and Data Processing

A. Participants

Thirteen young participants (age: 20-33 years, weight: 50.0-90.0 kg, and height: 158.0-175.0 cm, 7 males and 6 females) with no reported history of neurological diseases or lower limb injuries were recruited for the study. All the participants gave written informed consent prior to participation. This study was approved by the IRB Medical Committee of Peking University Third Hospital (IRB00006761-M2019164). Each participant was given a pair of smart insoles according to their shoe sizes (from UK 5.0 to 8.0). The software was running on an Honor 9X smartphone with two 2.2 GHz Cortex-A76 cores and Bluetooth 5.0 (Huawei Technologies, Shenzhen, China).

B. Plantar Pressure

Since the CoP position is calculated from the plantar pressure distribution, the accuracy of plantar pressure measurement by our system was validated first. The Footscan system (RSscan International, Olen, Belgium), which is generally considered as a gold standard of the plantar pressure measurement, was employed in the comparison test.

A walking test was implemented where the dynamic plantar forces were collected simultaneously by both the Footscan and our systems. Since the shoes can generally absorb and redistribute the plantar forces to the ground, which can greatly affect the Footscan's results, the participant was asked only to wear the insoles with his sockets on the outside. Also to avoid the relative sliding of the insoles during walking, the insoles were firmly attached to the bottom of the participant's bare feet with a double-sided tape. During the test, the participant was asked to walk through the Footscan force plate several times at his comfortable speed.

After the test, the data of both systems were synchronized by maximizing the cross-correlation of the two records, and the plantar pressure results of a complete gait cycle were extracted. Since two systems have different region definitions, the data of the insole system were reprocessed to match the definitions of data in Footscan, i.e., the anterior and posterior calcaneus data were combined to be compared with the heel data in Footscan, and the data of tuberositas ossis metatarslis V were selected to match with Footscan's midfoot data.

C. Static CoP

To verify the accuracy of static CoP measurement of our system and model, the ProKin 212 stabilometer (TecnoBody, Dalmine, Italy) was employed as the reference, which is shown in Fig. 7A. It can accurately evaluate postural control, the oscillation of CoP in AP and ML directions, as well as the area and perimeter of the latter.

The experimental procedure can be described as follows. Each participant was using the smart insoles with the same size as their shoes, which were set on top of the stabilometer's measurement platform. Before the test, the participant stood barefoot on the insoles, and both positions of the feet and insoles were carefully calibrated according to the stabilometer's requirements by an experienced therapist (see Fig. 7B). For the test, the participant was instructed to perform a one-minute double limb standing balance test with their eyes open. To test more thoroughly, the participants were asked to deliberate moving their center of mass as much as possible first to form an X-shape path and then a clockwise turn as shown in Fig. 7C. A timer was set to record the beginning and end time of each test which would be used for the data synchronization of the two systems.

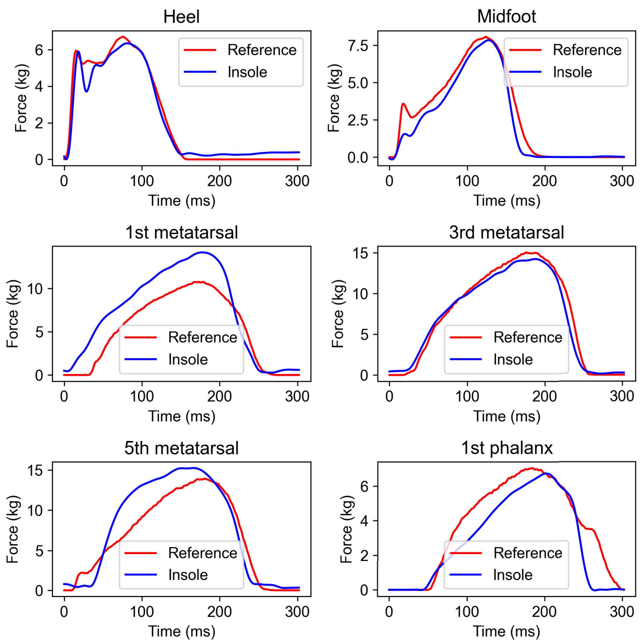

Fig. 8. The plantar forces at different locations detected by the insole and the FScan system as the reference during walking.

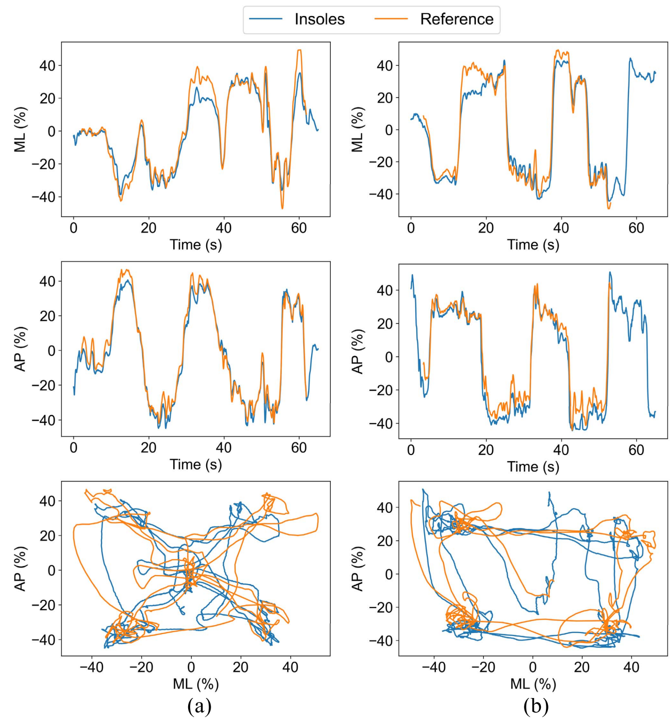

Fig. 9. The static CoP test results of (a) an X-shape path and (b) a clockwise turn.

The results of the instantaneous CoP displacement on both AP and ML directions were recorded by both systems. To evaluate the data agreement between the two systems, the intraclass correlation coefficient (ICC) was used, which could be rated as excellent (ICC from 0.75 to 1), moderate (0.4 to 0.74), and poor (0 to 0.39) [17]. And the paired sample t-test was employed to determine if there was a statistically significant difference between the results of the two systems.

V. Results and Discussion

A. Plantar Pressure

A typical set of dynamic plantar pressure results of a complete gait cycle measured by the Footscan and our systems is in Fig. 8. The overall results of our system agree reasonably well with those of the Footscan system. However, some locations have more differences, which may be due to the following reasons. First, some region definitions of the two systems are not the same, and the measuring areas are different even for the same location. The Footscan system defines a larger sampling region than ours and averages the overall pressure in this region. If the plantar pressure varies significantly inside a location, then the two results can have a larger difference, e.g., the 1st and 5th metatarsal. Second, although our insole is thin and flexible, it can still change the contact area shape. If the shape of a region is changed significantly, there can also cause a larger bias between the two systems, e.g., the 1st phalanx. For the regions with a regular shape and an evenly distributed plantar pressure, the results of the two systems showed a higher level of consistency, which indicates that our system has sufficient accuracy in plantar pressure sampling.

B. Static CoP and Balance

The results of a static double limb standing balance test are shown in Fig. 9, and the instantaneous CoP displacement is plotted in both AP and ML directions and a horizontal plane. Fig. 9A and B are corresponding to the two test models of changing CoP in an X-shape and a clockwise circle deliberately. It can be seen from the results that even though there were insoles placed between the feet and the platform (Fig. 7), the accuracy and the results of the stabilometer were barely affected. A high dynamic range and a fast response of the stabilometer were preserved in the results, which shows sufficient details and fast responses as CoP changes. By comparing the results of the two systems, no significant difference can be observed in both AP and ML directions. However, there is a relatively larger difference in the ML direction than in the AP direction. Such a difference is introduced by our simplified static CoP model, where the distance (s in Fig. 5) change was ignored. In a normal stand posture, the distance change in ML direction is larger than in AP direction, e.g., the distance between the forefeet can be different from that between the heels, while the distance in AP direction within each foot is almost the same. Such a difference change is less significant in a daily test when the user often has a larger distance between their feet than in this test. Additionally, the ICC and t-test results of all participants are summarized in Table I. From the table, the ICC values are well above 0.95 in the ML direction and above 0.9 in the AP direction, which indicates that our system is qualified for clinical usages (ICC $\geq$ 0.9). From the sample paired t-test, the CoP measurements of the two systems showed no statistically significant difference as the p-values are significantly above the threshold of 0.01. The overall results show that our system can achieve almost the same accuracy as the commercial equipment, but with much less cost, environmental restriction, and the required operation of a professional therapist.

TABLE I
THE STATISTICAL ANALYSIS RESULTS IN ML AND AP DIRECTIONS OF THE STATIC CoP TESTS

Index	ICC (ML)	p-Value (ML)	ICC (AP)	p-Value (AP)
1	0.993	0.999	0.901	0.812
2	0.965	0.844	0.950	0.884
3	0.967	0.977	0.974	0.981
4	0.972	0.969	0.937	0.993
5	0.973	0.980	0.967	0.964
6	0.986	0.969	0.978	0.982
7	0.990	0.886	0.979	0.797
8	0.980	0.283	0.951	0.620
9	0.993	0.977	0.949	0.768
10	0.978	0.901	0.960	0.942
11	0.987	0.967	0.973	0.913
12	0.987	0.979	0.962	0.974

p-value was from paired sample t-test assuming no statistically significant difference between two systems.

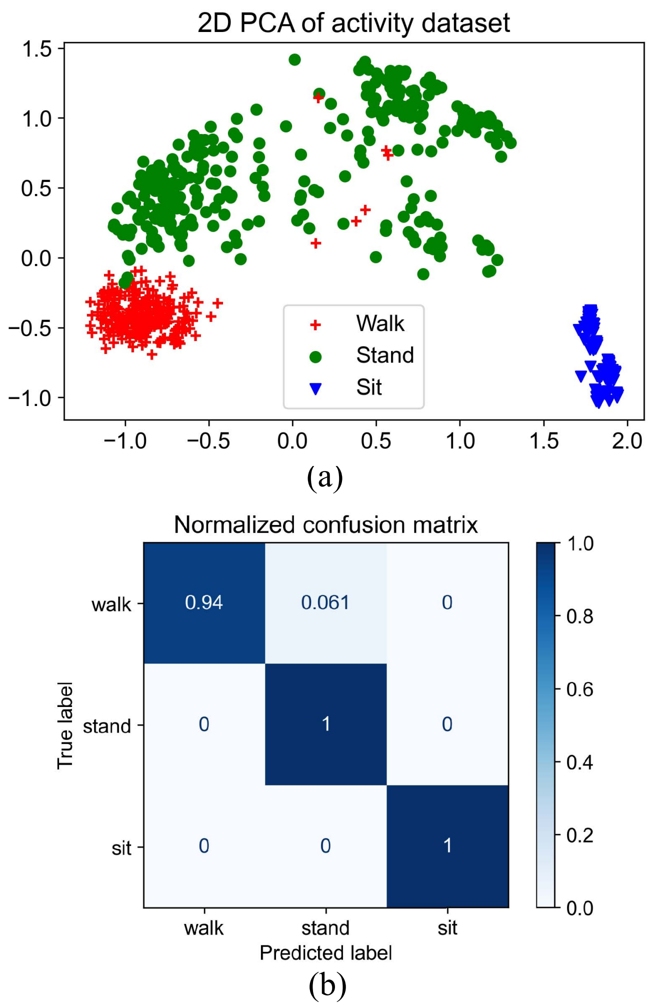

Fig. 10. The (a) plantar pressure distribution of different activities, and (b) activity classification result.

C. Activity Recognition

A total of 728 plantar pressure data samples were collected for all three activities, i.e., 288 walking, 312 standing, and 128 siting samples. To make results more general, we included 48 samples of walking up and down the stairs in the walking samples and asked the participants to exchange their support legs from time to time during the standing activity test. The distribution of the activity dataset through a 2D principal component analysis (PCA) is shown in Fig. 10A, where clear separations can be observed between classes. However, a few walking samples are overlapped with the standing samples, which may be due to the start and end of a walk test. In the training process, 80% of the data were randomly selected as the learning set, and the classification results of a multi-class RBF kernel-based SVM model are shown in Fig. 10B. The overall accuracy is 97.9%, which is sufficiently high comparing with other studies [16]. Other feature-based classification models have also been tested, including a random forest model (50 estimators with maximum leaf nodes of 5), a gradient boosting classifier (100 estimators with a maximum depth of 5), and a neural network (two hidden layers of 100 nodes). For the same training and testing sets, their accuracies are 97.9%, 97.2%, and 98.6% correspondingly. The neural network model has the highest accuracy, yet the overall accuracies are similar. It also indicates that the plantar pressures collected by our system contain sufficient information for human activity recognition. However, in this study, we only performed simple activity tests, i.e., each activity is pure and simple. In reality, human activities can be much more complex, e.g., cooking, washing clothes, where two or more activities and their transitions may be included. Therefore, the detection of complex activity and how to extract the CoP displacement from a complex activity may be an important topic in the continues CoP monitoring for our future study.

VI. CONCLUSION

In this paper, we developed a low-cost and high energy efficient sensor system for the long-term CoP monitoring in a smart-shoe form. It can measure the plantar pressure through multiple force sensors and present the real-time CoP traces through a user-friendly app on the smartphone. Additionally, a simplified static CoP calculating method was also developed without the requirement of exact sensor locations, which showed a good accuracy compared with the commercial device. Additionally, a human activity recognition model was incorporated to make the CoP monitoring process more automatic. In conclusion, our system has a good potential to be employed as a complement or replacement of the existing systems, especially in home and community environments.

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