A Sensor Placement Benchmarking Method with Principal Component Analysis

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***Abstract*—Foot plantar pressure measurements are valuable for diverse applications in clinical and biomedical studies. In-shoe devices have recently become popular and are considered effective tools for acquiring foot plantar pressure data thanks to their versatility. However, these devices are subject to low measurement resolution because only a limited number of sensors can be installed due to considerations of cost and comfort. Optimizing the sensor layout could be an effective solution to enhance the measurement quality. Contemporary devices rely either on an understanding of anatomy and practical experience or expensive data-driven approaches to configure the sensor layouts. In this work, we present a sensor placement benchmarking method that bridges the gap between the two aforementioned categories of methods and helps determine sensor layouts efficiently. The benchmarking method utilizes an open-access dataset to evaluate a sensor layout from multiple perspectives, including the accuracy of centre of pressure (CoP) estimation, prediction rate, sensor count and the physical insights generated from conducting principal component analysis on the dataset. Subsequently, the study demonstrates the method's functionality by applying it to the anatomy-based sensor layouts of two existing devices. Optimal sensor placements are identified, and general guidelines for sensor placement are proposed.**

***Index Terms*—Plantar Pressure Measurement, Rehabilitation, Sensor Placement, Gait Analysis.**

I. Introduction

FOOT plantar pressure measurements are an effective tool in various biomedical research domains. Relevant areas of study include biometrics [1], gait monitoring [2], rehabilitation training systems [3] [4] [5], ergonomic footwear design [6], and disease diagnosis [7] [8] [9]. Standard instruments employed for obtaining and analyzing foot plantar pressure data comprise platform [10] [11] and in-shoe systems [12] [13] [14] [15] [16] [17] [18] [19] [20] [21]. Platform systems are designed to be fixed on the floor of a laboratory environment and measure the plantar pressure when the users step on them. They consist of a large array of pressure-sensing units. In-shoe systems are designed to be worn by the user and typically carry many fewer sensors.

In-shoe systems offer advantages over platform systems in many scenarios due to their versatility. They can collect a large dataset that reflects a person's gait pattern. The devices, integrating pressure sensors within soft and flexible cushioning materials, require a comfortable, lightweight design [22], [23], [24]. The design must also have minimal system complexity and low production costs [25], [26]. Therefore, an insole should accommodate a small number (around 10) of pressure sensors for several reasons: 1) the utilization of rigid materials in pressure sensors, which may cause discomfort; 2) the complex circuitry ~~design~~ necessitated by an increased number of sensors, potentially compromising system versatility; and 3) the additional weight imposed by extra pressure sensors and the related electronics. The disadvantage of having a low number of sensors is reduced measurement spatial resolution and, very likely, decreased accuracy. Consequently, it is crucial to explore strategies for enhancement.

Optimizing sensor layouts is one potential way to improve measurement quality in in-shoe devices with a restricted number of sensors. Various pressure-sensing insoles have been developed, as seen in [20], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36]. Among these works, different strategies have been employed to determine sensor placement. Most sensor layouts rely on anatomical knowledge and experience [20], [27], [28], [29], [30], [31], [32]. This approach has limited generalizability to a wide variety of feet, as it considers a generic foot model. Simultaneously, quantitative validation of the layouts is rarely provided. Experiments involving a small number of test subjects are also frequently utilized for sensor location selection [33], [34], [35], [36]. Although they provide the rationale for selecting the sensor locations, these experiments vary largely from each other and still show a deficiency in quantitative validation concerning the accuracy of pressure measurements. Recently, ~~several~~ data-driven methods have been proposed to generate near-optimal sensor layouts [26], [37]. However, these methods may not be implemented due to insufficient data, time, computational power, experiment venue, and high-end data acquisition instruments. A method bridging the gap between anatomy-based and data-driven strategies is required. This method needs to efficiently evaluate various sensor layouts before the integration.

A key challenge is the absence of evaluation methods targeting sensor layouts in in-shoe systems. Existing studies frequently assess the effectiveness of the systems as a whole after the fabrication of the device [16], [20], [38], [39], [40], [41], [42]. Some studies incorporate pressure measurements, including peak and mean pressure, to evaluate device performance [16], [20], [38], [39]. However, these pressure measurements depend highly on sensor parameters like sensitivity, range, and hysteresis. Thus, they focus on the performance of individual sensors rather than the overall sensor layout.

A commonly used metric for assessing the measurement accuracy of the overall sensor layout is the centre of pressure

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(CoP) trajectory. The metric reflects essential gait characteristics such as mean velocity and has been used to assess fall risk [43], [44], [45], [46], [47]. A few studies compared different sensor layouts by assessing the accuracy of CoP estimation to a high-resolution platform system [20], [40], [41], [42]. The metric is also employed as the decision variable in the cost function of the previously mentioned data-driven methods [26] [37]. Muñoz Organero et al. [48] utilized the change in the CoP when one sensor is left out to determine the relative importance of sensor positions within a pre-defined location set. In their attempt to compensate for the error in in-shoe measurement systems by implementing an algorithm, Saggin et al. [49] also employed the CoP error as one of the objective variables. ~~Consequently, CoP trajectory estimation should be employed as an effective benchmarking parameter in evaluating the performance of a sensor layout.~~

Other metrics for sensor positioning have also been implemented. Smith et al. [50] considered peak plantar pressure locations to position force-sensing resistors for identifying gait phases.

The prediction rate is a metric that can be considered in parallel to ensure the validity of the CoP estimation accuracy. For instance, a sensor layout with sensors solely distributed in the heel region will generate precise CoP estimations during the heel strike phase. However, it will not record any pressure value when the heel is lifted off the ground while other foot areas are still in contact. In this case, the CoP calculation will result in the output of a null value, which is difficult to be incorporated into the calculation of overall CoP estimation accuracy. Ignoring the null values would result in a misleadingly low estimation error. ~~Some aforementioned~~ Studies employ different metrics to treat this issue. The algorithm presented in [26] minimised a variable measuring the correlation between different sensor locations, thereby preventing densely clustered sensor layouts. Research such as [20], [40], [41], and [42] did not address this aspect, as they primarily focused on anatomy-based sensor layouts that were originally sparsely distributed. Nevertheless, a metric that accounts for the aforementioned phenomenon needs to be included to analyse a broader range of sensor layouts. The prediction rate, which calculates the ratio of data frames with valid results to the total number of data frames, effectively achieves this objective.

Another metric neglected by existing studies is the sensor count. As previously mentioned, a low sensor count reduces system complexity and cost and increases comfort and versatility. To the author's knowledge, while sensor count is usually considered an important factor, no existing literature incorporates it as a formal benchmarking parameter. Neglecting this parameter makes comparisons between sensor layouts with different numbers of sensors incomplete.

This study proposes a benchmarking method aimed at the efficient evaluation of sensor layouts during the early stages of in-shoe plantar pressure prototype development. The method considers several aspects, including the accuracy of CoP estimation, prediction rate, and sensor count. At the same time, the method performs principal component analysis (PCA) on an open-access plantar pressure dataset [51] collected with a high-resolution platform system. The data processing technique allows users to evaluate the sensor layouts based on different metrics. An example of how the benchmarking method can be applied to two anatomy-based sensor layouts is provided. Ultimately, a sensor placement guide is produced based on the investigations on the two systems.

II. Methodology

A. The Benchmarking Method

The objective of this method is to assess the performance of a given sensor placement. An open-access plantar pressure dataset comprising 55 healthy individuals [51] is utilized, of which the details are presented in section II-B. The method addresses the previously mentioned difficulty of comparing the performance of sensor layouts with varying numbers of sensors. The method also allows the users to deduce the appropriateness of the sensor placement from the pressure data by inspecting the outcome of PCA. The PCA first loading coefficient matrix (LCM) reflects the significance of different foot regions, helps identify sensor redundancy and inspires new sensor locations. The method is depicted schematically in Figure 1. Initially, the dataset is processed according to the procedures described in Sections II-B1 and II-B2. Subsequently, CoP trajectories can be calculated from the high-resolution dataset as a reference. Then, the chosen sensor positions are manually mapped onto the accumulated pressure footprint derived from each individual's data. Estimated CoP trajectories can be generated using the sensor placement information, and the average error of estimation can be calculated across all test subjects. Next, PCA is conducted on each subject's data, consisting of 24 stance phases, to obtain the first LCM. Finally, the evaluation is performed using the following: 1) Numerical measurements: CoP estimation accuracy, prediction rate, sensor count. 2) Physical interpretation of the sensor placement with LCM.

B. The Dataset

The dataset is provided by the CAD WALK project [51] and contains walking data for 55 healthy individuals. Twenty-four trials are conducted for the left foot of each subject. Each trial contains plantar pressure distribution maps for a complete stance phase of walking and consists of approximately 300 to 400 frames of pressure mapping data.

A 0.5 m Footscan plate (rs scan, Paal, Belgium; dimensions: 48.8 cm $\times$ 32.5 cm) with a Kistler force plate (0286AA, Kistler, Winterthur, Switzerland) placed underneath was used to collect the plantar pressure measurements. The instruments were synchronized by an RS Scan Footscan 3D interface box. The measuring frequency of the plantar pressure data was 500 Hz. A few data frames are shown in Figure 2 as an example.

1) Preprocessing: The Footscan plate constitutes an array of pressure sensors with non-square dimensions of 7.62 mm $\times$ 5.08 mm. As a result, when plotted on a uniform grid, the footprints appear to be compressed in the anterior-posterior direction. To get around this problem, upsampling was conducted utilizing bilinear interpolation. Normalization was used to eliminate the differences between participants. The preprocessing procedure is shown in Figure 3. ~~The left foot~~

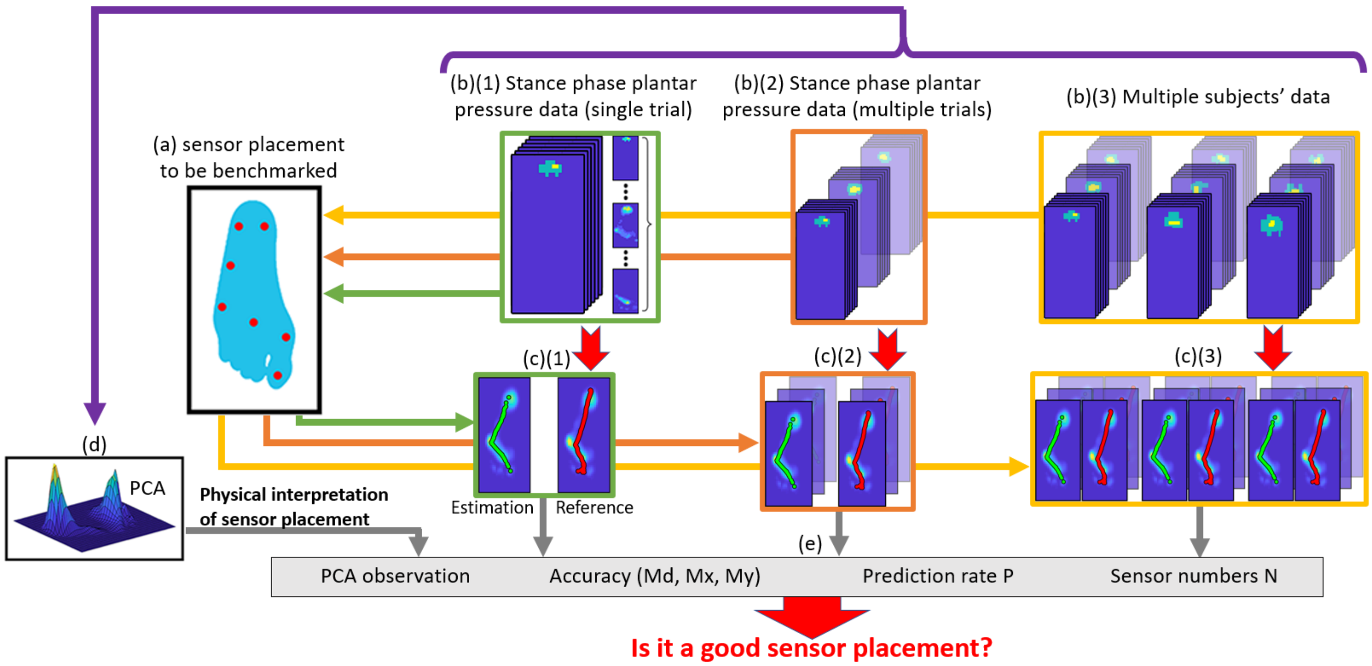


Fig. 1. A schematic diagram of the method. (a): The user supplies the sensor placement to be benchmarked by marking the sensor locations onto the accumulated footprints of the dataset. (b)(1-3): Three different sizes of datasets can be incorporated: single trial (b)(1), multiple trials from the same subject (b)(2) and multiple subjects (b)(3). (c)(1-3): For each trial, CoP trajectories estimation can be generated with the sensor layout, and reference CoP trajectories can be computed from the dataset. CoP estimation accuracy can be obtained through comparison. (d): PCA is applied to the datasets to obtain the first LCM to extract physical insights. An LCM is computed for each subject through a process described in Section II-D and Figure 4. (e): Benchmarking metrics, including the PCA observation, CoP estimation accuracy, prediction rate and sensor numbers, are used to determine the quality of the sensor placement. Additional accuracy parameters extended from M_d, M_x and M_y are incorporated to assess the layout's repeatability with the multiple-trial dataset and the generalizability across a large population with the multiple-subject dataset.

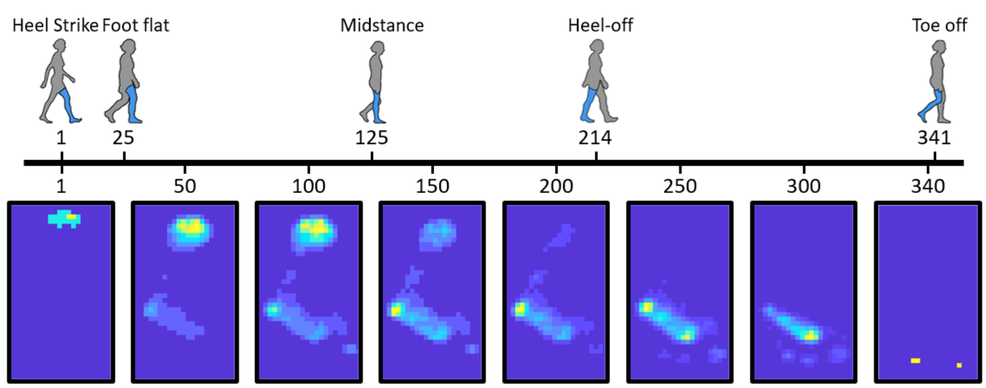


Fig. 2. Example of data frames within a trial. As the stance phase progresses from heel strike to toe-off, the plantar pressure pattern changes.

~~footprints seem to be from the right foot due to the formatting configuration of the data-processing software.~~

2) Alignment Method: Due to the natural variations in walking patterns, the pressure footprints belonging to the same subject can vary in orientation and position trial by trial. An alignment method was developed so that all trials of a subject can be matched in position and orientation, as shown in Figure 3. The alignment method takes inspiration from the footprints normalization method devised by Nakajima et al. [52]. A reference trial is randomly selected from a subject's 24 trials. The orientation and position of the other trials for the same subject are matched to the reference trial. The method is illustrated in Figure 3.

C. Benchmarking Metrics

1) CoP Estimation Accuracy: As previously mentioned, the centre of the pressure trajectory serves as an index containing crucial gait information. A low-resolution in-shoe system that generates CoP trajectories closely matched with the reference CoP trajectories generated by a high-resolution platform system suggests a high performance. Therefore, a sensor placement that generates a low average CoP estimation error is considered a good sensor placement. The CoP reflects the location of the normal reaction force exerted on the plantar surface of the foot at a particular instant. Its location

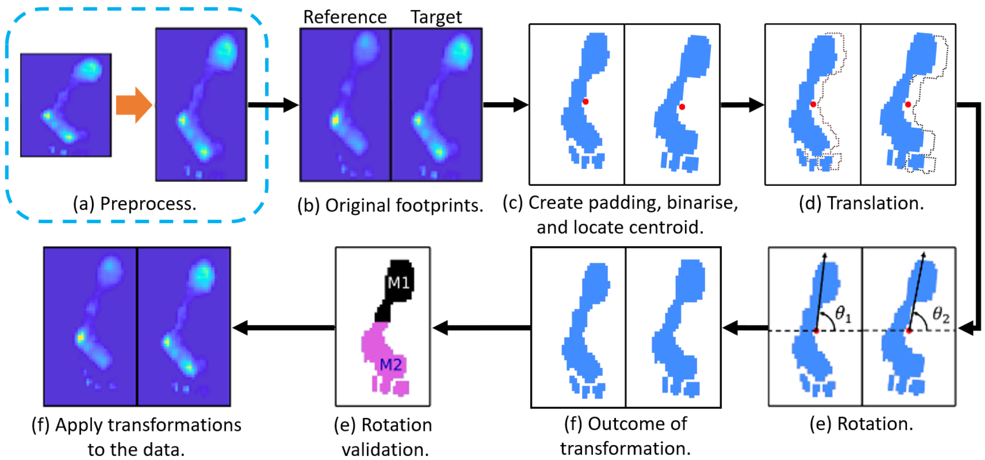


Fig. 3. The data processing procedure for a subject's data: (a) Preprocessing involves normalisation and linear interpolation. (b) A trial is randomly chosen to produce an accumulated pressure footprint, which serves as the reference against which other trials are aligned. (c) The size of the target footprint is adjusted to match that of the reference. Empty pixels are added around the image to avoid insufficient space for translation. Then, the footprints are binarised with a logical filter. The centroids of the binarised images are located. (d) The footprints are translated to move the centroids to the centre of the images. (e) Rotation: SVD analysis is applied to both footprints to obtain the principal axis and its angle with the horizontal axis. Rotate the right footprint so that the two angles match. (f) The transformation outcomes. (g) Rotation validation: Due to the SVD algorithm's characteristics, the principal axis can point in the opposite direction, causing an inverted matching footprint. Compute the mass of the upper and lower halves of the right binarised footprint. The rotation is valid if the bottom half possesses a higher mass due to the human foot structure. Otherwise, a further 180-degree rotation is applied. (h) Apply the identical transformations to all the frames in the target trial.

$(x_{\text{CoP}}, y_{\text{CoP}})$ can be calculated as:

$$(x_{\text{CoP}}, y_{\text{CoP}}) = \left(\frac{\sum_{i=1}^{m} x_i\, p_i}{\sum_{i=1}^{m} p_i}, \frac{\sum_{i=1}^{m} y_i\, p_i}{\sum_{i=1}^{m} p_i} \right) \tag{1}$$

where p_i is the pressure measured by the sensor located at position (x_i, y_i). The x-direction is taken to be mediolateral (medial, positive), and the y-direction anteroposterior (posterior, positive). m is the total number of sensors.

The following metrics M are proposed to measure the CoP estimation accuracies in the x- and y-directions:

$$M_x = \frac{\sum_{j=1}^{m} |(x_{\text{low}})_j - (x_{\text{ref}})_j|}{m} \tag{2a}$$

$$M_y = \frac{\sum_{j=1}^{m} |(y_{\text{low}})_j - (y_{\text{ref}})_j|}{m} \tag{2b}$$

where the subscripts ref and low indicate the positions of the CoP found using data from a reference high-resolution platform system and a lower-resolution in-shoe system, respectively. The metric for Euclidean distance, M_{d}, is

$$M_{\text{d}} = \frac{\sum_{j=1}^{m} \sqrt{[(x_{\text{low}})_j - (x_{\text{ref}})_j]^2 + [(y_{\text{low}})_j - (y_{\text{ref}})_j]^2}}{m} \tag{3}$$

M_{d} provides a view of the overall geometrical error of a CoP estimation. M_{x} and M_{y} facilitate analysis on the two respective directions.

While the reference trajectory is computed from the dataset, the sensor-generated estimated CoP trajectory can be obtained in a few steps: 1) Produce a binary mask with value equal to 1 at the selected sensor locations. The sensor size is set to 1 pixel to be consistent with other similar studies such as [26] and [37]. 2) Apply the binary mask to the data frames of the same trial. 3) Compute the CoP for each frame.

The parameters utilized to evaluate the accuracy of CoP trajectory estimation are:

- $\overline{M}_x$, $\overline{M}_y$, $\overline{M}_{\text{d}}$: the average estimation errors for all N subjects, calculated over all data frames for which a CoP can be calculated.
- $(\overline{M}_x)_Q$, $(\overline{M}_y)_Q$, $(\overline{M}_{\text{d}})_Q$: the average estimation errors excluding the top Q% of subjects with the largest errors in M_x, M_y, M_{d} respectively. Q is set to be 10% in this work. The parameters serve to eliminate the effect of extreme values from the sample population.
- E_5, E_{10}: The percentage of subjects who achieve an M_{d} within 5 mm and 10 mm.

2) Prediction Rate: There can be instances that, despite the foot still being in contact with the ground, the in-shoe device records no pressure value due to its low sensor count. In this case, the CoP cannot be estimated, and a null value is generated. The proposed prediction rate P can be used to quantify how often this occurs. For a given trial t, P_t can be defined as the percentage of data frames for which a CoP can be estimated. For a high-resolution platform system, P_t should nearly always equal 100%. For a low resolution sensor system, P_t is very likely to be less than 100%. The parameter P is significant because a low average CoP estimation error, as quantified by the metrics $\overline{M}$, can occur in two ways: Either the sensor measurements can be used to calculate an accurate CoP for all data frames, or the sensor measurements calculate an accurate CoP for some data frames and no CoP for all other frames (because all sensor readings are zero). The second scenario suggests an unsatisfactory sensor layout. The prediction rate serves to identify such instances.

To calculate the average prediction rate $\overline{P}$ for N subjects, each with T trials:

$$\overline{P} = \frac{1}{N} \sum_{n=1}^{N} \left(\frac{\sum_{t=1}^{T_n} P_t}{T_n} \right) \tag{4}$$

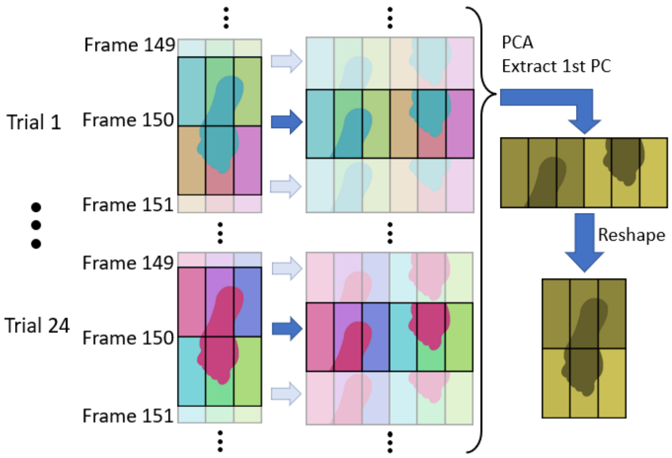


Fig. 4. The data concatenation and processing procedure. Fictional frames of data are shown for illustration purposes. The pressure maps from all the trials are converted into vectors and concatenated in a single dataset. The dataset undergoes PCA, which extracts the first LCM. Finally, the LCM is reshaped.

3) Sensor Count: As previously mentioned, the number of sensors N is an important factor.

D. Principal Component Analysis (PCA)

PCA, a method to extract important information from a piece of data [53], forms part of the evaluation method to extract valuable insights on the pressure distribution across multiple stance phases. As illustrated by Figure 5(a-d), the reconstructed data is highly similar to the original data.

To process the multiple-stance phase plantar pressure data of a subject, several steps are involved as shown in Figure 4: 1) The data from each frame of all the trials are rearranged into row vectors. 2) The vectors are stacked together. 3) PCA is applied to extract the first LCM.

From observation, the LCM displays the shape of a foot in the x-y plane. The z dimension represents the loading coefficient for the preprocessed pixels, with higher z magnitudes indicating more critical pixels. Consequently, the peaks and troughs signify crucial regions where optimal sensor locations are hypothesized to occur.

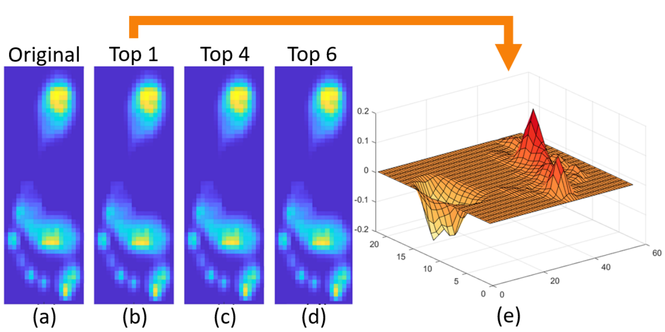


Fig. 5. PCA: (a) shows the original accumulated footprint from the data of a stance phase. (b), (c), (d) utilizes the top one, top four and top six principal component and loading coefficient pairs to reconstruct the footprint. From observation, the first component-coefficient pair extracts sufficient information and is therefore utilized in our method. (e) shows the first LCM.

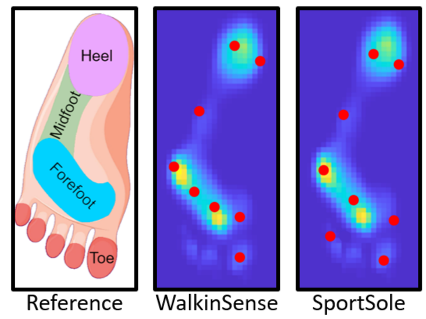


Fig. 6. WalkinSense [32] and SportSole [29] sensor placement presented on accumulated plantar pressure footprints with reference to the foot structure. Due to the variation of foot shape and structures across individuals, the placements are manually arranged by observing the plantar pressure data. Conventionally, the placements are determined by experience and an inspection of the foot. The difference results in both placements performing better with the availability of plantar pressure in this study compared to the real-world scenario.

III. Case Study with Existing Anatomy-Based Sensor Placement

Two existing systems depicted in Figure 6 are employed to examine anatomy-based sensor placements.

The first system, referred to as WalkinSense [32], selects sensor locations based on previous research [54] [55]. The second system, named SportSole [29], positions sensors beneath the calcaneus, the arch, the head of the first, third, and fifth metatarsals, the hallux, and the toes. The sensor placements are marked on the footprint of subject one in Figure 6.

A. Midfoot: Lateral Arch

Test 1: remove the arch sensor

The first experiment investigates the sensor placed at the lateral arch, a shared feature between WalkinSense and Sportsole. The lateral arch is identified as one of the 15 ideal sensor locations based on anatomy [20]. However, by inspection of the first LCM of 55 test subjects, the lateral arch is rarely a prominent region. For example, Figure 5(e) shows an LCM with a non-prominent arch region. The observation suggests potential redundancy of the arch sensor for some feet.

Modified WalkinSense and SportSole sensor patterns are produced by removing the arch sensors. The comparison between the modified and original placements yields results in Table I. Although modified placements possess higher $\overline{M}_{\mathrm{d}}$ and $(\overline{M}_{\mathrm{d}})_Q$, the deterioration is below 11%. For WalkinSense, only 14/55 subjects showed a deterioration of over 10% in $\overline{M}_d$, 13/55 showed deterioration within 1%, and 7 showed no effect. For SportSole, only 11/55 subjects showed a deterioration of over 10%, 29/55 showed deterioration within 1% and 9/55 showed an improvement. Also, a relationship between the LCM and the importance of the arch sensor was found with an example shown in Figure 7. Subject 12 showed little error difference with a non-significant LCM arch area, while subject 42 had a large error difference with a significant LCM arch area. Consequently, the following conclusions can be drawn: 1) The arch sensor is redundant for most of the able-bodied sample population. 2) Its importance in measurement accuracy

TABLE I
THE BENCHMARKING RESULTS OF DIFFERENT MODIFICATIONS OF THE SENSOR PLACEMENTS. THE MODIFIED PLACEMENTS ARE COMPARED TO THE TWO RESPECTIVE ORIGINAL PLACEMENTS AND THE CHANGES ARE RECORDED IN PERCENTAGE. THE IMPROVEMENTS ARE HIGHLIGHTED IN GREEN AND THE DETERIORATION IS HIGHLIGHTED IN RED.

				Accuracy			Prediction Rate	Sensor Number	Generalizability				
Base placement	Test	Region Investigated	Modification	$\overline{M}_d$ (mm)	$\overline{M}_x$ (mm)	$\overline{M}_y$ (mm)	$\overline{P}$	N	$(\overline{M}_d)_Q$ (mm)	$(\overline{M}_x)_Q$ (mm)	$(\overline{M}_y)_Q$ (mm)	E_5 (mm)	E_{10} (mm)
WalkinSense			None	7.69	3.12	6.47	96.7%	8	7.21	2.88	6.05	0.0%	90.9%
SportSole			None	7.87	3.33	6.47	96.7%	8	7.49	3.12	6.15	0.0%	89.1%
WalkinSense	1	Arch	Arch sensor removed.	+9.1%	+2.0%	+11.1%	+0.0%	-12.5%	+8.5%	+1.4%	+10.0%	+0.0%	-12.0%
SportSole	1	Arch	Arch sensor removed.	+7.5%	+5.7%	+7.1%	+0.0%	-12.5%	+9.2%	+7.8%	+9.1%	+0.0%	-8.0%
WalkinSense	2	Heel	Two heel sensors realigned.	-6.6%	-12.0%	-5.8%	+0.1%	+0.0%	-5.8%	-11.5%	-5.2%	+3.6%	+4.0%
SportSole	3	Toe	Sensor near central toe region removed.	+0.9%	-0.6%	+1.8%	+0.0%	-12.5%	+1.2%	-1.2%	+2.3%	+0.0%	+0.0%
WalkinSense	4	Forefoot	Use 3 forefoot sensors instead.	+11.3%	+13.2%	+10.8%	+0.0%	-12.5%	+11.8%	+14.0%	+10.9%	+0.0%	-12.0%

is heavily dependent on the prominence of the arch area in the LCM.

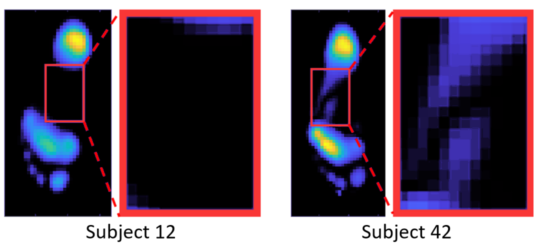


Fig. 7. The LCM of subjects 12 and 42 with zero values shaded in black. Subject 12 has a flat LCM arch region. The removal of the arch sensor resulted in minimal impact on the estimation accuracy. On the other hand, the impact was significant on subject 42 with a prominent LCM arch region.

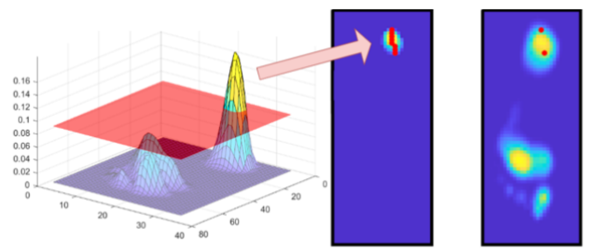
B. Heel

An investigation was conducted regarding the sensor redundancy in the heel region. From observation, the heel region of the LCM is usually a hill with a single peak. It is hypothesized that a single sensor placed at the LCM heel peak can achieve similar CoP estimation accuracy. However, an investigation showed that ~~the~~ $\overline{M}_y$ heavily deteriorated. Significant estimation errors occurred in the heel strike phase. With only one sensor activated in the heel strike phase, the CoP is forced to stay at the sensor position.

Test 2: two sensors aligned in the AP direction

Based on the ~~experimental~~ results with a single heel sensor, we hypothesize that aligning the sensors in the AP direction will be more effective. The exact location of the second heel sensor is determined by an automated process comprising the following steps as shown in Figure 8:

1) Figure 8(a): A contour filter is applied to the principal component to extract the heel region. The filter finds a height level where 90% of the volume of the LCM is contained below. The 90% threshold is obtained from experiments. A scan is performed in the X dimension to find the most prominent pixel for each Y value. A path is generated.



(a) Apply height level filter to generate the path. (b) Sensor position.

Fig. 8. The process to select the locations of the two heel sensors. (a) A height level filter is applied to the LCM so the heel area can be segmented. A path is found by finding the maximum point for every Y value. (b) The two ends of the path are selected as the sensor positions.

2) Figure 8(b): Sensors are placed on both ends of the path.

This approach ensures the two sensors are sparsely distributed along the AP direction.

After realignment, 34/55 subjects showed an average of 1.3 mm improvement in $\overline{M}_d$, 20/55 showed an average deterioration of 0.8 mm, and one subject remained unchanged. More results are shown in Table I. The average CoP estimations improved in all aspects for most of the subjects. At the same time, it is the only sensor placement that allowed positive E_5 and E_{10}. The following conclusions for the heel region can be drawn: 1) A single sensor at the LCM peak would result in a slightly worse X-direction CoP estimation but a significant deterioration in the Y direction. 2) Two sensors aligned in the AP direction results in a better overall CoP estimation.

C. Toe

This section investigates the performance of sensors placed in the toe region.

Test 3: one sensor vs two sensors

SportSole features two sensors in the toe region: one under the hallux and another near the third and fourth toes. From observation, the hallux is usually much more prominent than the other toes on an LCM, suggesting that the fourth toe sensor can be removed with little impact in estimation accuracy.

After modification, the difference in $\overline{M}_d$ is 0.16 mm, and the variance of error difference is 0.07 mm. The results show a minimal difference in estimation accuracy. Therefore, the sensor around the fourth toe makes a negligible impact on the overall performance and should be removed to save cost.

D. Forefoot

Both reference systems place many pressure sensors within the region, four for WalkinSense and three for SportSole. The LCM for most test subjects displays a highly prominent forefoot region.

Test 4: three-sensor vs four-sensor configuration

We evaluate the performance of the three-sensor configuration seen on WalkinSense and the four-sensor configuration seen on SportSole. To cancel the effect of other sensors, the experiment modifies the WalkinSense placement by replacing the two sensors at the centre of the forefoot region with a single sensor at the average position of the two.

As expected, the four-sensor configuration achieved higher performance.

IV. A Sensor Placement Guideline

The guide presented in Table II is based on results from Table I and experiments in sections III-A to III-D. Assuming preprocessed plantar pressure data for at least one stance phase is available, we begin with the WalkinSense sensor placement (Figure 6) and make modifications according to the data.

V. Discussion

The study presents a sensor placement benchmarking method designed to be utilized to efficiently evaluate sensor layouts in the early stage of developing an in-shoe plantar pressure device. The method bridges the gap between the conventional anatomy-based sensor placement strategies, often unvalidated, and the data-driven algorithms that are usually infeasible due to the requirement of advanced instruments, a laboratory environment and computational resources. Applied to two existing anatomy-based sensor layouts, the method showed the ability to discover sensor redundancies and suggest more optimal sensor locations in various foot regions from both numerical and physical perspectives. A sensor placement guideline was produced as a result. However, the method has its own designated use cases and limitations.

TABLE II
A sensor placement guide for each foot region.

Foot regions	Guide
Lateral Arch	1) Observe the lateral arch region on the LCM. 2) Remove the sensor if the region is not prominent.
Heel	1) Find the location of the peak of the heel region on the LCM. 2) If two sensors are used, realign them in the AP direction using the steps described in section III-B.2.
Toe	A second toe sensor does not appear to be necessary.
Forefoot region	Three sensors may be adequate in this region.

Among the five sets of alternative sensor layouts generated, one achieved better overall results with the same sensor count, and four resulted in slightly worse results with one less sensor. It is justified to argue that the overall improvement in the two anatomy-based sensor layouts is modest. However, the investigations yielded important observations along the way. For example, Section III-A concludes that the arch sensor is redundant for many subjects but highly prominent for the rest of the population, depending on the physical interpretation of their LCMs. Users can leverage this finding by determining the category to which they belong and subsequently deciding to include an arch sensor based on their needs. Section III-C suggests that the sensor near the central toe region has minimal impact for nearly all subjects.

Also, the study is limited in generating significant insights into the forefoot region, which constitutes a relatively large area. Due to its high importance, future research should focus on conducting more experiments and observations on the forefoot region.

The efficacy of the proposed benchmarking method, when applied to subjects with foot abnormalities, remains to be investigated. No evidence was provided so far as the method only utilizes a dataset of healthy individuals. However, ~~the author believes that~~ the method should yield equal to or better results on subjects with foot irregularities if a suitable dataset is incorporated. The reason is that conventional anatomy-based sensor layouts are based on a generic healthy foot model, which means they cannot effectively consider any irregularities, resulting in potentially worse performance than application on healthy subjects. On the other hand, the method could investigate the irregularity conditions more comprehensively due to incorporating a plantar pressure dataset. Nevertheless, the study provides a foundation for future research in this area.

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