PneuShoe: A Pneumatic Smart Shoe for Activity Recognition, Terrain Identification, and Weight Estimation

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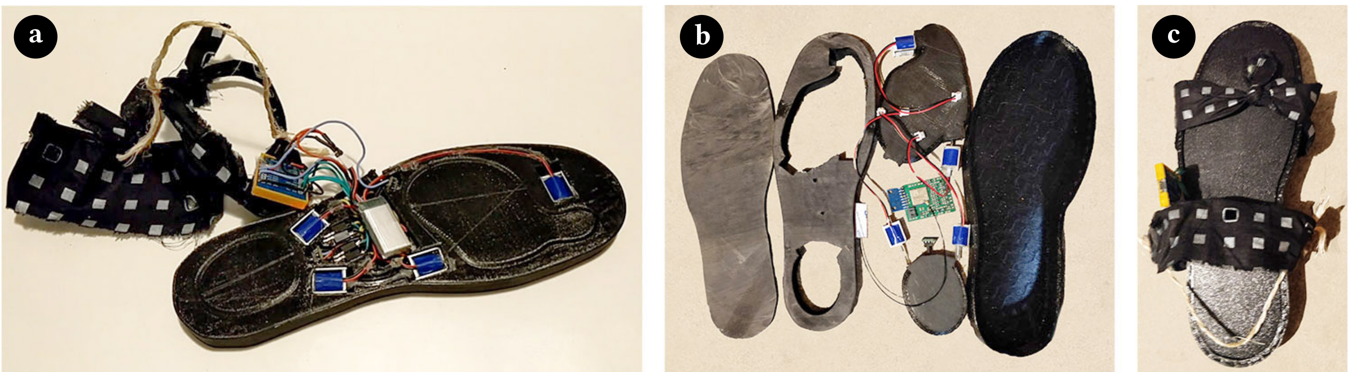

Figure 1: Our prototype is a 3D-printed smart insole. In the equipped with two air chambers connected to electronic valves, as well as air pressure sensors. A microcontroller drives the pressure valves as well as sensor data from an accelerometer. a) Back-side of the prototype, b) Layers, how they are assembled, c) Top view of the assembled prototype.

ABSTRACT

We present a footwear prototype that can detect activities, distinguish terrains, and estimate the user's weight. The insole features two air chambers with pressure sensors and a 6-DOF IMU. A machine learning model, a decision tree was trained to distinguish standing, walking, and running. Further, we can discriminate between differentiate terrains, such as soft sand, asphalt, and grass. Moreover, we showcase how the air pressure sensors can be utilized to provide a weight estimation.

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Applied computing** → Health informatics.

KEYWORDS

Human Augmentation, Pressure, Sensor, Terrain, Wearable

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1 INTRODUCTION

In recent years, there has been an increasing interest in foot interfaces [9]. For accurately detecting gait and related parameters, literature showcased a great number of technology approaches, which include the following sensors: Inertial Measurement Units (IMUs) for measuring movements, rotation, and angular velocity [18, 22], Pressure sensors for measuring ground contact and calculating the center of pressure [11, 12], Temperature and humidity sensors for monitoring diabetic foot ulceration [25, 26], Strain gauges for recognizing stretch, bend, and changing pressure [5], Speed sensors for calculating physical forces [19], GPS for tracking location, height differences, speed, and distance, Capacitive sensors for detecting walking styles, foot gestures, and floor type [15, 23], Infrared light sensors for measuring heat and blood flow, and detecting blood sugar [6, 7, 14], Microphone sensors for determining gait parameters [29, 29] and Cameras for tracking of posture and gait, and detecting terrain [2, 3, 30].

We propose a different method for detecting user data, such as their activity, ground information, and user weight. Our developed artifact has particularly two air chambers with pressure sensors to measure change evoked by the wearer. We validated our artifact through three small experiments.

In this paper, we contribute an artifact with the capabilities to:

- differentiate between different activities such as: standing, walking, and running,
- identify different undergrounds such as grass, soft sand, and asphalt,
- estimate weight.

2 PROTOTYPE

In this research, we present an artifact *(Figure 1)* and our development process to build our device.

2.1 Chamber System Layout

The position of these chambers is important to measure meaningful data at different areas of the foot. Matthies et al. [24] already showed which areas might be of interest. We added to their figure 2 our design (e), which shows the images of plantar pressure combined with a heat map. In our design, the toe and metatarsal are building one chamber and the heel the other chamber. The best positions are the peak pressure points of the foot during movement. During normal walking activity, the front and back foot touches the ground at different times. First the heel absorbs the kinetic energy and then the foot gets rolled to the front and the front gets pushed against the floor to generate the forward movement.

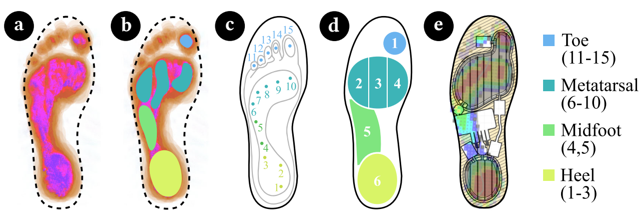

Figure 2: a-d) Areas of interest determined by Matthies at al. [24] and Shu et al. [27]. e) Displaying our design.

2.2 Material of the chambers

A normal 3D-Printer is able to print a wide range of Filament[28]. The chambers need to be airtight and flexible, to build up sufficient pressure and change the chamber properties. Some papers[10, 13, 21, 31] printed an insole by using Ninjaflex from Ninjatek. This TPU is soft and tough. In 2021 this company released a new filament, called Chinchilla. Chinchilla is much softer. However, various tests of this material showed that it was not tough enough for air pressure or the resistance needed for human body weight. Other materials investigated, such as hard TPU were too brittle, the use of Ninjaflex seems most appropriate. Ninjaflex was used for the chambers, while Chinchilla was used for the frame and insole.

2.3 Sensors & Electronics

For the proposed approach, the air pressure of the chambers needs to be measured. The absolute sensors will compare the pressure in the chamber with a fixed pressure of the sensor. Additionally, an IMU will be integrated to measure movement and rotation. For fast prototyping we selected Arduino as a cost-effective platform [1]. The prototype in this paper uses an ESP32, because of its compactness, compute power, connectivity, and robustness. Figure 1(b) shows all the components and the PCB. One of the pressure sensors is under the PCB, the object with blue tape is a valve and the blue-chip on the left side of the PCB is the IMU. On the PCB are nine mosfet stages and the power supply and the ESP32.

2.4 Technical Insights

Pressure Chamber Material: Fused Deposition Modeling (FDM) 3D printing does not inherently produce airtight pressure chambers without post-processing. Such post-processing may involve smoothing and sealing the surface by melting it, or applying a coating of another material, such as rubber paint. The 3D printer's built-in capability to 'iron' a print was found to be insufficient.

Microcontroller: The ESP32 is a well-designed microprocessor making it perfect for an IoT device. Even in deep sleep, the ESP can take measurements, saving them to an SD Card or flash storage. In normal operation mode, uploading the data if a connection is present is possible. Using the FreeRTOS is strongly recommended, because of the real-time features incorporated. This includes precise timing functions and the scheduler. System Queues can be used to guarantee consistency in data of independent program tasks.

Ripple Reduction: The electric noise from inductive loads on the power line of the microcontroller can be reduced with a MOSFET-Stage, consisting of diodes, resistors and capacitors, presupposed the actuator has only one direction.

3 EVALUATION

We conducted three pilot studies aiming to answer the following research questions: *"RQ_{Pilot1}: How can we detect different activities relying on air pressure data?"*, *"RQ_{Pilot2}: How can we detect different terrains using both, air pressure sensors and the IMU?"* and *"RQ_{Pilot3}: How well can we estimate the user's weight using the air pressure sensors only?"*

3.1 Pilot Study 1: Activity Recognition

3.1.1 Hypotheses. To answer our research question, we establish the following hypothesis:

H1: As the prototype is able to sense pressure, we will be enabled to detect different ambulation activities, such as walking, running and standing.

3.1.2 Apparatus. The device as proposed is used. Particularly, the pneumatic pressure sensors are used in this study. The prototype's IMU and vibration capability are not used in this study. The web interface running on the ESP32 is used to visualize and stream the data to a client.

3.1.3 Procedure and Task. We invited the participant and asked for oral consent. Then, the participant was made to wear the prototype. The participants were videotaped, to check the performance in a post-processing manner. For this, the data was synced by the study leader. Each participant was instructed to walk a distance of 20 meters in one direction, turn around, and then run back along the same 20-meter stretch. This sequence was performed three times, with a brief pause of 5 seconds between each round.

3.1.4 Participants. In this pilot study, we invited three participants.

- Gender: Female, Age: 21 yrs, Weight: 82 kg, Height: 163 cm, Shoe size: 39EU
- Gender: Male, Age: 27 yrs, Weight: 76 kg, Height: 178 cm, Shoe size: 42EU
- Gender: Female Age: 43 yrs, Weight: 90 kg, Height: 170 cm, Shoe size: 40EU

3.1.5 Data Gathering. This study primarily utilized quantitative data derived from pressure sensor measurements at the front and rear sections of the smart insole. To facilitate temporal pressure variation analysis, a synthetic value was incorporated, computed as (baseline = baseline0.999 + sensorValueH0.001// 1000Hz). Additionally, data from six axes of the IMU were recorded. All these measurements, together with a timestamp, were captured at a frequency of 100 Hz. The entire test was filmed with a 60 Hz camera. We performed an additional post-processing on the data before extracting synthetic features representing abrupt pressure variations. Specifically, instances where the sensor reading in the rear chamber (sensorValueH) exceeded the baseline by 50mv were flagged. When the pressure fell below the baseline by 50mv, the corresponding time difference was computed and stored.All measurements were manually labeled as standing, walking, or running with the aid of the video footage. The final set of measurements included approximately 180 meters of walking, 162 meters of running, and 60 seconds of standing. The duration of the running phase was shorter due to the inclusion of a one-meter start time and a one-meter distance to decelerate.

3.1.6 Results and Discussion. The aim of this study was to develop a real-time classification system to run on the microcontroller. 'Weka'[16] found the time difference between pressure increase and decrease to be the most significant feature and generated a J48 decision tree, a variant of the C4.5, with a theoretical performance of 99% accuracy. A substantial advantage of the decision tree is the straightforward implementation in C-Code:

```
if (millis() - lastStepStart > 2101) {
    classification = "standing";
} else if (millis() - lastStepStart > 1028) {
    classification = "walking";
} else {
    classification = "running";
}
```

3.2 Pilot Study 2: Terrain Detection

3.2.1 Hypotheses. Based on previous findings shown in CapSoles [24], two hypotheses are established:

H2: It can be assumed that a smart sensor shoe can differentiate between hard and soft undergrounds.

H3: The consistency of measured IMU values on hard undergrounds is higher than on soft undergrounds.

3.2.2 Apparatus. We predominantly utilized data from the Inertial Measurement Unit (IMU) sensor. Like the previous prototype, these data were captured at 10 ms intervals and were then streamed into a cloud-based InfluxDB database. We chose not to employ the vibration and valve system in this particular study. Our prototype differs from the one presented in CapSoles [24] in several ways. While the CapSoles prototype incorporates capacitive sensors, it lacks an IMU. Furthermore, our prototype boasts a higher sampling rate of 100 Hz, compared to the 30 Hz sampling rate of CapSoles.

3.2.3 Procedure and Task. The evaluation procedure starts with explaining the task. We gathered consent from the participants and collected their biometric data. Right after, the participants were asked to put on the prototype and to take a few steps, getting a feel for the shoes and the wear. On our end, these steps are also used to check the prototype's functionality. The participant then started the task. The participants were asked to walk on a randomized order of terrains for 20 meters, then turn around in the middle of the track and repeat this 3 times. The measured terrains range from soft to hard, sand, grass and asphalt.

3.2.4 Participants and Data Gathering. We used the same participants from study 1 (*see subsection 3.3*).

This study is grounded on the data from the air pressure sensors. Additionally, we utilize data from an accelerometer and a gyroscope in three dimensions, thus enabling us to measure foot movement. We collected data from three different surfaces, with each session lasting 35 seconds. This resulted in a total of 315 seconds of data, which, at a recording frequency of 100 Hz and eight measured values per cycle, equates to a dataset of 252,000 individual values.

3.2.5 Results and Discussions. The phase during which the foot maintains ground contact was identified as the most informative. We observed varying degrees of foot stability across different terrains. Ground contact is defined as a 50mv increase in pressure in any of the chambers, a determination method consistent with our previous study. Only measurements obtained during these ground contact phases will be subject to analysis.

The raw data of a single step can be seen in figure 3. The first graph shows the standing phase on asphalt. The measured values on asphalt appear nearly stable. The second graph shows grass, the sensor values shoe to be less stable compared to asphalt. The final terrain, sand, yielded "shaky" or unstable measurements. A simple threshold classifier, based on a C4.5 decision tree, was applied to the signal ripple (the sum of changes from one sensor reading to the next, normalized to the same value range and number of samples) across all six IMU values. This approach was capable of differentiating the samples with an accuracy of 100%, provided that the samples were preprocessed. Typically, the first and last two steps are discarded due to their incomplete nature. Therefore, hypotheses H2 can be accepted, since the ripple is noticeably higher. Hypothesis H3 can be accepted as well, as the ripple on the soft underground is much more inconsistent than on hard asphalt. Although we have a small sample size, we postulate that the system can differentiate between diverse undergrounds by the stance time. On soft undergrounds, the stance times are longer (sand: 800ms, grass: 730ms) than on hard surfaces (asphalt: 670ms).

3.3 Pilot Study 3: Weight Estimation

3.3.1 Hypotheses. Previous studies have shown that a weight estimation with smart insoles is somewhat possible. Hellstrom et al. [17] utilize a Force Sensitive Resistor (FSR) ESS310 plus a FlexiForce adapter 1120 with a wearable insole to showcase a weight estimation. In a broader study, Kim et al. demonstrate a weight estimation

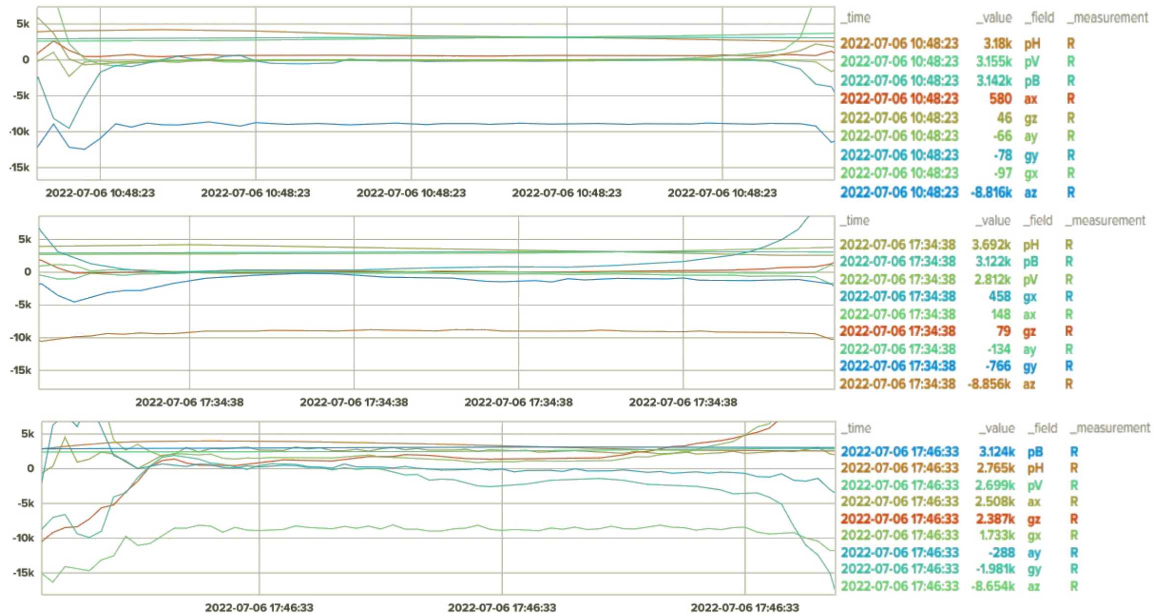

Figure 3: Sensor values of the three surfaces, top: Asphalt, middle: Grass, bottom: Sand. pH: Pressure Heel, pV: Pressure Ball, pB: pressure Baseline, ax: accelerometer X, gz: Gyroscope X, ay: accelerometer Y, gy, gyroscope Y, gx: gyroscope X, az: accelerom. Z

with a broad dataset by 72 different users using a MobileNetV2 Neuronal Network [20]. Although FSR show a substantial sensor drift, D'Arco et al. [8] neural network approach for weight estimation. Therefore, we establish two hypotheses are established:

- **H4:** The air pressure sensors embedded inside the insole will be the optimal sensor to capture the physical information to further analyze and predict weight.
- **H5:** A neuronal network may be the most useful and efficient way of finding the hidden pattern of the relationship between air pressure from the insole and the weight.

3.3.2 Procedure and Task. Each participant was asked to step on a weight measure to gather ground truth data of the user's current weight. As next, the participant was asked to step with their left foot onto the left insole, while keeping the right foot in the air. This task was repeated five times for each test subject.

3.3.3 Participants. In this experiment, more than 37 different people were invited to participate in the data collection. They are between 18 and 40 years old and come from Europe, India and China. The foot size was between 37 and 45 EU.

3.3.4 Apparatus and Data Gathering. The insole prototype was sampled with 100 Hz. The ground truth was collected by a commercial weight measure. At this time, the shoe size was also measured, since we suspect the shoe size to influence the distribution of the weight to the pressure chambers. Two pressure points (pV - front chamber sensor / pH - rear chamber sensor) were collected over five seconds per trial *(see Figure 4)*. The data gathering was similar to the previous studies. We ended up with 185 data points and 37 data sets.

3.3.5 Results and Discussions. We selected a machine learning approach and therefore split our collected data into two groups (80% training and 20% test set). We tested several window sizes, including 100% (6000ms) down to 13% (800ms). We ran trained a neuronal network for regression with spectral features of the raw data. The neural network has an input layer with 3 features and 2 dense layers with 10 neurons each and an output layer. We experimented with different numbers of training cycles (epochs). We used a loss function as a criterion to find the optimal epoch value to minimize the prediction error. We found that the loss function decreased from 195.06 to 85.07 as the epoch value increases from 100 to 1000. After all the parameters are set to be optimal, which is, setting the spectral Analysis as processing block, setting window size as 6000ms - a single window approach and 800 as training cycles and 0.05 as learning rate, the final model of accuracy is 70.97% with the mean squared error of 85.08 and loss as 155.21.

In this research, we discovered that the use of smart insoles for weight estimation is feasible. However, the weight test accuracy for testers in this experiment was approximately ~70%, leading us to reject hypotheses H4 and H5. We propose using pneumatic pressure sensors for this application since this technology does not exhibit the typical sensor drift seen in Force-Sensitive Resistors (FSRs). According to the datasheet of the pressure sensor, the Long-Term Stability over 1 year is approximately 0.5% [4]. In future studies, it would be compelling to explore whether the user's weight could also be reliably estimated during motion, such as walking. For the scope of this study, a linear regression may be a more fitting approach for standing, and a load cell might be preferable. However, for running, the approach presented in this study could be suitable.

4 CONCLUSION

In this paper, we demonstrated a pneumatic smart insole. We conducted three studies answering three research questions that we can conclude with a positive result as follows: RQ 1) A precise activity recognition of ambulation activity is possible by relying on air pressure data only. It is even possible to reconstruct the gait cycle with two pressure chambers only. RQ 2) Terrain identification is

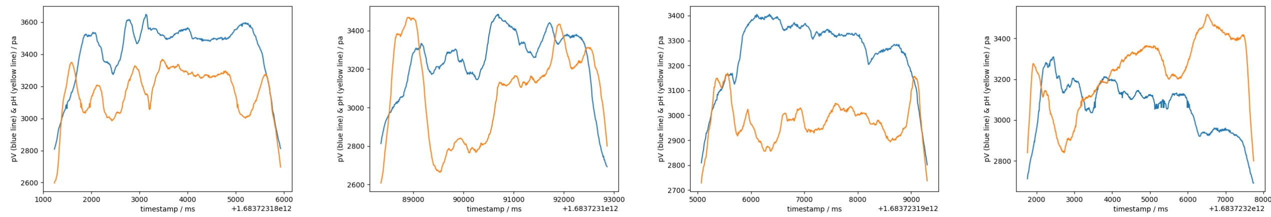

Figure 4: Raw data of P14 (78.55 kg) showing pV, pH over time. In our experimental setup, the participant stepped on the insole five times (four times depicted here). The raw data makes it obvious that a machine learning approach seems necessary.

possible using IMU data. Different terrain shows alternating speed in gait. With softer terrain, the stance time showed to increase. The stance time was increased on grass over asphalt and even more increased on soft sand. RQ 3) Finally, we were able to estimate the user's weight using a pressure chamber system. These findings may yet not be generalize, but confirm internal validity.

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