ShoeTect: Detecting Body Posture, Ambulation Activity, Gait Abnormalities, and Terrain with Multisensory Smart Footwear

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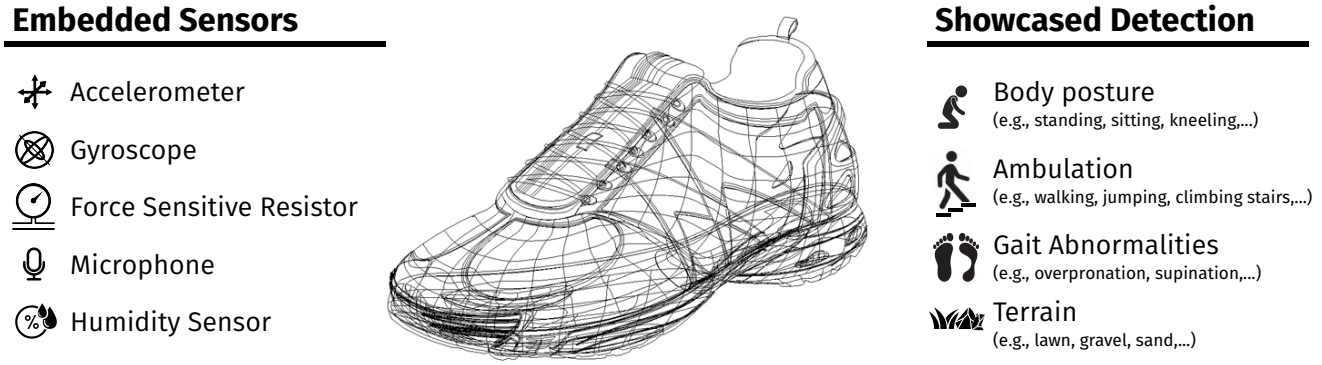

Figure 1: We propose a proof-of-concept shoe that demonstrates the capability of detecting relevant user and context information by a multi-sensory approach. In future, an assistive smart shoe can help to enable a healthier lifestyle by detecting unhealhty body postures and walking conditions, as well as dangerous behaviors, such as a too long running on unfavourable terrain. In addition, many other applications are conceivable.

ABSTRACT

Our feet are not just used to walk upright, feet can also reveal important context information on our physical constitution and context. In this research, we present a proof-of-concept multisensory approach to uncover the hidden information our feet hold. We instrumented a shoe with an accelerometer, a gyroscope, FSRs, a microphone, and a humidity sensor, while we drove a conventional machine learning approach. Our results show that we are capable to extract information on body posture (e.g., standing, sitting, kneeling), ambulation activity (e.g., walking, jumping, climbing stairs), gait abnormalities (e.g., overpronation, supination), and terrain (e.g., lawn, gravel, sand). These insights may show a new direction for the future of smart shoes.

CCS CONCEPTS

• **Human-centered computing → Ubiquitous and mobile computing systems and tools**.

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KEYWORDS

Smart Shoe, Assistive Augmentation, Proof-of-Concept, Multi-Sensor Approach, Wearable Computing, Machine Learning, Data Mining.

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1 INTRODUCTION

About 1.5 million years ago, humans became bipedal. While walking upright engenders various advantages, there are also significant trade-offs that we might be unaware of. One drawback is the loss of a valuable interaction channel, which we believe, should be regained as evolution moves towards the Cyber-Human [10]. The availability of advancing technology that is becoming increasingly mobile and wearable, could enable an extension of human's interaction capabilities through an assistive smart shoe [83]. Using the foot as an alternative position for providing feedback is now being explored in modern Human-Computer Interaction (HCI) research [58, 86]. Also having a look at input through feet is of interest in HCI [29, 87]. In fact, the feet is already utilized to control technical systems, such as a car, a sewing machine, or a desktop computer [79]. Interaction gestures are either based on foot ankle movements, the bending of the knee, or hip movements [87]. Sensing foot activity often requires a cumbersome wearable instrumentation of the foot,

such as with optical markers [80] or an environment that provides a sensing apparatus such as a gas pedal or a pressure sensitive floor [13, 55]. Exploring augmented foot interfaces have experienced increasing interest during the years as nicely summarised by Elvitigala et al. [27]. In particular smart insoles became more prevalent in the field (~60% of all published papers since 2013) [27]. Apart from the use in HCI the main applications for augmented foot interfaces include gait analysis with the aim to provide treatment for medical conditions. This form factor seems to be preferred because of its discreteness making it a socially acceptable wearable device similar to a smartwatch. Another advantage of using insole-based foot augmentation is the high availability of shoes. An instrumentation of a shoe using insoles has already been demonstrated in decades with orthopedic insoles that offer increased quality of life. Making insoles smart by embedding an intelligence can significantly support humans in achieving daily goals, such as for tracking workout performance [14] or using it as input interface for VR [53]. These previous approaches are not yet what we believe an assistive shoe could be capable of.

Therefore, in this paper we contribute with an artifact [91] that reveals how a multi-sensory approach can be utilized to discover the relevant information on body posture, ambulation activity, gait abnormalities, and terrain.

2 RELATED WORK

In 1988, Pearson and Weiser already investigated the use of foot input for computers [70]. While pressure-based gestures are sufficient for simple input [63], research also demonstrates that toe-based, heel-rotation-based [80], and foot-tapping gestures [24] are possible. Alexander et al. further investigated the mapping of foot-gestures to real-world applications [3]. Other works focused on the idea of combining foot and hand input [43, 50, 76]. A popular interface to detect foot gestures are pressure floors, which rely on various technologies, such as optical sensing (e.g. via FTIR) [7, 13], piezoelectric sensing [66], or resistive sensing (e.g. via FSRs) [75]. While using hands is more common in VR environments, such as CAVE-like-installations [25], Beckhaus et al. [12] believe that hands-free navigation can maximize interactivity in VR. To gain a reliable foot input, Higuchi and Nojima [41] proposed shoe's sole tracking. With the rise of VR, researchers proposed a variety of approaches [11, 23, 53] to utilize foot gestures, such as walking in place and locomotion in 3D scenes to increase immersion. While foot interaction is not novel, wearable technology features insoles, which have been investigated for more than three decades [40, 59, 60]. Within this period, previous research mainly focused on: analyzing gait to study disabilities [1, 6, 9], measure performances [32, 67, 73], and explicit foot gestures as a control for computers [11, 18, 23].

Meanwhile, plantar pressure measuring insoles rely on different technologies [85] (e.g. capacitive sensing [21, 42, 59], resistive sensing [1, 6, 11], piezoelectric [35, 40, 52], strain gauge [45, 60], conductive polymer [9, 89, 92], air pressure [47], EFS [9], EMFI [37], flexible switches [18], etc.). The main research objective concerned gait analysis for rehabilitation treatment [1, 6, 45]. However, new generation pressure-measuring smart insoles yield more potential, enabling workout activity tracking [28], high precision detection of walking speeds [36], the recognition of dangerous foot poses, unhealthy back postures [28], and a variety of healthcare applications [26]. Other applications with insoles, demonstrate a unique user authentication while walking [56] or through the individual footprint [55], or even inferring on the users' stress level [29]. These examples highlight the tremendous information feet yield, worthy of future exploration.

2.1 Body Posture Detection

Visual computing techniques are one of the major methods to detect body posture. Particularly, RGB cameras and infrared cameras provide the required input signals. To implement posture identification, a view-independent framework was proposed by Liu et al. [49], which is based on viewpoint rotation transformation using a Microsoft Kinect. By extracting features and evaluating performance, five representative postures have been demonstrated to be estimated accurately.

Due to the desire for portability and efficiency, smart devices are progressing towards miniaturization and intelligence. Sensors are applied in various fields to detect external information because they possess features of miniaturization and digitalization. Ribeiro et al. [74] developed an intelligent sensing chair prototype. Pressure sensors were embedded into eight air chambers and placed on different parts of a chair. Twelve different sitting postures can be identified from the gathered data. Other sensor types, such as, fiber optic sensors are becoming favored in wearable device development due to their unique performance. In He et al. [39] study, they developed a detection method based on fiber optic sensors. By simplifying the lower limb as a two-link rigid body model and attaching the fiber sensor to the lower limb of subjects, dynamic postures can be identified.

Incorrect body posture may harm the human body. McLean et al. [57] indicated that prolonged sitting can contribute to chronic muscle and vertebral column diseases. Further, Grandjean and Hünting [34] illustrated that bad standing postures are sometimes accompanied by pains in muscle and connective tissues. Using a smart shoe prototype to determine incorrect body postures have been demonstrated for workout in a gymnasium by Elvitigala et al. [28]. The prototype features a pressure sensitive insole based on FSR technology.

2.2 Ambulation Detection

Lara and Labrador [48] categorised human activities, such as walking, running, jumping, etc. as ambulation activities. These activities are somewhat different to posture, as they exhibit human movements. Some movements show greater motion and an increased load on joints and muscles than others, creating very distinctive characteristic information.

In many studies, video-based equipment is typically used to record and analyze these movement patterns [2]. A general drawback is that such equipment is expensive and the covered range is limited, usually to a laboratory environment. Therefore, the usage is limited to certain types of studies.

With the development of embedded systems and wearable smart devices, monitoring human movement is becoming more convenient and economical. Due to the portability and integrity of the embedded system, movement identification can be conducted in a wide range of situations. The accelerometer has been verified

as feasible for movement and posture monitoring [33]. In Santos et al. [77] study, a low-cost wireless system composed of eight IMU nodes was developed to identify ambulation activity. Other wearable devices are also appropriate for movement identification. Haescher et al. [36] use capacitive pressure sensors in their study to build smart insoles for classifying different walking activities.

The information derived from ambulation activity or characteristic foot movements can infer on the user's mental state as Elvitigala et al. [29] shows. Such information can be further applied to avoid safety hazards. In the study of Antwi-Afari et al. [4], a safety hazard identification approach was proposed, namely, by applying a wearable insole pressure system.

2.3 Gait Detection

Gait is often referred to a plantar pressure and leg movement pattern that varies among individuals and develops over people's lifetime [8]. In the 20th century, gait analysis started to be used in clinic applications and became widely used following the advent of modern computers. In modern clinic applications, physical conditions and neurological conditions can be diagnosed by analyzing the gait and thus classified as an indicator for assessing health status.[78]

As gait analysis has received more concern, some gait detection methods have emerged. These methods can be generally categorized into two types: kinematics-based and kinetics-based methods. Kinematics-based methods focus on the spatial-temporal variables while kinetics-based methods focus on the moments and forces during the dynamic process [15]. Caldas et al. [16] applied the kinematics-based method in their study. In using IMU to investigate the impact of speed and inclination to gait, and applying the self-organizing maps (SOMs) algorithm, different gait patterns were classified in accordance with kinematic features. This method is also used by Wang et al. [88]. By applying an inertial sensor and film-pressure sensors combined with gait analysis algorithm, spatial-temporal gait parameters were estimated.

Different from kinematics-based methods, GRF is often considered a vital parameter in kinetics-based methods and is widely applied in gait detection studies. In the study of Park et al. [68], an insole with FSRs was designed to detect the GRF. By examining the change in the center of pressure (COP), real-time gait detection can be implemented. Senanayake and Senanayake [81] classified walking gaits into two main phases and eight sub-phases. Based on the concept of the gait phase, some GPDSs were proposed by Pappas et al. [65] [64]. Gyroscopes and FSRs were used in GPDSs to access the angular momentum and plantar pressure. By analyzing the data, four gait phases: stance, heel-off, swing, and heel-strike can be detected. In the study of Chen et al. [20], an intelligent shoe-integrated system has been designed by applying FSRs to particular areas and calculating the average plantar pressure for gait detection. A similar approach, using a fuzzy logic was deployed by Kong and Tomizuka [46]. In addition to the use of FSRs, there are some studies that use other electronic components. For instance, capacitive sensing is used more frequently [5, 69]. Very recently, Matthies et al. [54] showed how to correct gait with a smartshoe-like system.

2.4 Terrain Detection

Different terrains show different characteristics. Some appear to be harder, such as cement pavement, than others, such as meadow. When a person walks or runs on changing terrains, the variation of feedback caused by the terrain may lead to different gait, and thus, varying performances.

According to a number of studies, walking patterns seem to change when people move on a slippery surface. This is verified by Whitmore et al. [90]. The authors showed that people unconsciously change their walking mode in order to maintain their balance slippery ground surfaces. Cham and Redfern [19] also noted that humans may adjust their walking pattern to minimize the potential risk of falling. Gait and landing time changes to reach the required coefficient of friction on the slippery terrain. Cappellini et al. [17] also stated that people adopt a slower walking speed and a shorter stride length on slippery surfaces. Zrenner et al. [93] showed that a change in rotation and angular velocity appears to be a factor when identifying terrains.

Footwear in the present market is currently unable to retrieve context information around the user. However, there are some research prototypes that reveal ways to extract context information with sensor around or in the shoe. Matthies et al. [56] developed a smart insole prototype that demonstrated the feasibility of terrain identification. Their prototype is based on capacitive sensing, which considers a certain ground-coupling portion that contains information on the underground. Also utilizing capacitive sensing, Cheng et al. [22] presented a study which shows that the distinction between meadow and concrete surface can be estimated by analyzing the occurring difference in sensor readings during walking cycles. Using an accelerometer, Otis and Ménélas [62] proposed another method to determine physical properties of the ground. Besides these studies, Eskofier et al. [30] proposed a hall sensor to monitor the ground's magnetic field.

In 2021, Elvitigala et al. [27] published a comprehensive survey on foot augmentation interfaces. This review states that research on smart footwear and related commercial products is continuously expanding. The expansion is due to the fact technology has decreased in size, yet increased its capabilities. In contrast to related work that focuses on a single investigation, in this paper, we would like to sketch a more complete vision of a smart shoe that demonstrates a variety of sensing capabilities.

3 SHOETECT

This section elaborates upon our proof-of-concept. Before providing technical details on our prototype, we outline the usefulness of such an assistive smart shoe by elaborating on example scenarios.

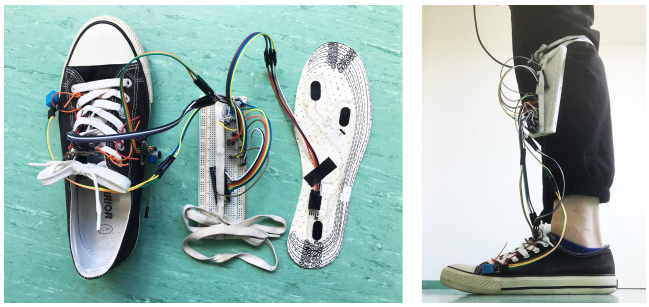

Figure 2: The prototype (left) and in worn state (right)

3.1 Envisioned Scenarios

1) Prolonged sitting and sedentary office work can create tiredness and thus cold feet, given the different cyclation of blood. An augmented foot interface with an actuator can sense such temperature changes at the foot, and thus infer the user's mental state to deploy various interventions. Two types of potential interventions are envisioned: a) decreasing the user's comfort levels to initiate a state change, such as encouraging the user to stand up, or b) creating comfort through heat, in which the slight and gradual temperature change would not be perceivable.
2) An augmented foot interface can sense external ground changes, such as uneven terrain, while a user is walking or running and provide potential counter-actions, such as tightening the shoe to the foot or changing the properties of the shoe's sole, through adjusting cushioning, stiffness, or pronouncing an outer sole profile for increased comfort and injury prevention. Alternatively, the insole becomes raised in certain areas (e.g., heel) resulting in a sub/unconscious weight shifting of the foot which invokes a change to a healthier posture.
3) Acute stress is becoming a common symptom of our increasingly sedentary lifestyle. Distinct foot movements and certain foot postures can evidence acute stress, which can be recognizable using an augmented foot interface. A subtle poking under the foot reminiscent of a massage sensation can be used to create awareness and may reduce the stress level.
4) Feedback through a poking sensation at the feet can provide notifications to the user while engaged in hands-busy scenarios, such as carrying bags, holding onto bus rails, pushing carts, device interaction etc. Receiving incoming notifications, such as a phone call, through a poking sensation at the foot releases other interaction channels and allows unobtrusive notification responses. Rejecting phone calls with a quick foot gesture, such as a stamping, can make us more effective and expands our input throughput, as feet become an additional interaction channel, similar to the hand.

3.2 Prototype

The ShoeTect prototype is based on kinematic, kinetic and feature detection methods, and performs multiple identification functions by detecting plantar pressure, foot acceleration and angular momentum, and other information. The following sensor are implemented:

- **Force sensitive resistor (FSR) insole**: A three-zone FSR insole by LEGACT is used. In accordance with the study of Shu et al. [82], these three FSRs are distributed in the heel area, metatarsal-midfoot area, and metatarsal-toe area. By applying the three-zone FSRs insole, the plantar pressure on these areas can be monitored. Besides, the thickness of the FSRs is 0.4mm and the trigger force is 100g, which ensures the directness and rapidity of force transmission. The resistance of FSRs without trigger can reach 10 MOhm, and output resistance will change in accordance with the pressure in the range of 100g to 10kg. In order to detect the plantar pressure, a voltage divider circuit was used in this study.
- **Accelerometer and Gyroscope through an Inertial Measurement Unit (IMU)**: By analyzing the acceleration and angular momentum, the moving pattern and stability of the foot can be estimated. In this study, the Adafruit LSLSM6DS33 IMU module is tied to the front of the shoe tongue and above the upper shoe through four symmetrical shoelace holes.
- **Microphone Sound Sensor (MSS) module**: Since the condition of ground differs, the hardness and roughness can also be different. Considering that, the loudness of sound when stepping on different terrains may be different. Therefore, an MSS module is used to monitor the loudness of stepping sound. The MSS KS0035 sensor module is tied to the side of the shoe through two side holes.
- **Digital Humidity and Temperature (DHT) sensor**: The humidity of the terrain may be a factor for the terrain identification. Therefore, a DHT11 sensor is also tied near the outsole to monitor the ground surface humidity (*see Figure 2*).

All these modules are connected to an Arduino Nano board, and the circuit board is connected to a laptop via a mini-B USB cable and powered by the laptop. Some resistors and wires are plugged onto a breadboard. The Arduino Nano board and breadboard are tied to the leg.

3.3 Data Processing

The data stemming from the FSRs insole, IMU module, MSS module, and DHT11 sensor are transmitted from the Arduino Nano board to a wired laptop. Through a Python script, the data was stored in CSV files for post-processing (*see Table 1*). The normal walking speed for humans is one to two steps per second, and the running speed is three to five steps per second. In accordance with the study of Senanayake and Senanayake [81], each step can be divided into a maximum of eight phases. Therefore, one second can be divided into nearly forty sections. Based on this, a more than sufficient sampling rate of 50Hz was set.

3.4 Classification

In this study, we relied on a post-processing machine learning method with a conventional classification task. In rudimentary pretests, we could confirm the Random Forest (RF) classifier to provide most reliable results, and thus, this classifier was used. The RF uses multiple deep decision trees to reduce variance and improve

Table 1: Collected data: The data instances are constituted with twelve attributes.

Attributes	Meaning
Accel x	Accelerometer x-axis data
Accel y	Accelerometer y-axis data
Accel z	Accelerometer z-axis data
Gyro x	Gyroscope x-axis data
Gyro y	Gyroscope y-axis data
Gyro z	Gyroscope z-axis data
Analog toe	Analog signal of the FSR (Toe area)
Analog plantar	Analog signal of the FSR (Midfoot area)
Analog heel	Analog signal of the FSR (Heel area)
Analog microphone	Analog signal of the MSS module
Humidity	Digital signal of the DHT11 sensor
Class	Posture (body posture identification) Ambulation (movement identification) Gait (gait identification) Terrain (terrain identification)

model performance [38]. RF is based on and improved over the bagged trees. The bagging prediction average is shown as Equation 1 and standard deviation is shown as Equation 2, where X_i and Y_i are given training set and response set, f_b is the classification or regression tree, and x' is unseen sample. To improve the performance of random forest, for classification with p features, a random sample of m predictors is chosen at each split, where $m = \sqrt{p}$. Due to such an improvement, the test error and out-of-bag error are reduced [44].

$$\hat{f} = \frac{1}{B}\sum_{b=1}^{B} f_b(x') \tag{1}$$

$$\sigma = \sqrt{\frac{\sum_{b=1}^{B}(f_b(x') - \hat{f})^2}{B-1}} \tag{2}$$

3.5 Model Training & Testing

Datasets are divided into a training set and a test set. The training set is used for modeling, and the test set is used to crosscheck the validation of the model. We selected a cross-validation as a statistical analysis method used to verify the performance of the classifier. This method is also used to improve the generalization ability by reducing the over-fitting phenomenon. The k-fold cross-validation is one of the most applied methods here. In this method, the dataset is divided into $k-1$ average sets. Each set is regarded as a testing set, while the other $k-1$ sets are regarded as the training set. Therefore, $k-1$ sub-models can be derived. The average classification accuracy will be calculated as the final result. In this study, we use both, a 10-fold cross-validation and a 50% percentage split validation.

4 EVALUATION

The goal of this study is to explore whether we can extract user and context information from our shoe prototype. By using a conventional data mining approach to classify the data, recognition functions and predictive analysis simulations will be ran.

These research questions will guide us through the evaluation while answered by each following subsection:

RQ1 *How accurate is a body posture detection?*
RQ2 *How accurate is a detection of ambulation activity?*
RQ3 *How accurate is a gait identification?*
RQ4 *How accurate is a terrain detection?*

4.1 Body Posture Identification

Posture is the appearance of a human's body. Certain body postures are common in life, such as standing, sitting, and kneeling etc. We suspect that the plantar pressure in different postures can differ. Besides, the foot angle may also be different. Considering that, foot postures can be used to analyze the body postures.

4.1.1 Study Design. In this study, 5 participants were asked to accomplish predefined tasks for the data gathering. The tasks and instructions are shown in Table 2. All the postures are foot-involved. Participants included males and females, whose shoe sizes were between 37 and 42 (EU size), and thus, suitable to use the prototype. They were asked to maintain different task postures for about 15 seconds, which ensure enough data for data mining. In order to ensure that participants maintained a relatively uniform sitting posture, they sat on the same chair to conduct the sitting test. To avoid environmental interference, all the tests were conducted on the same linoleum ground in the same building. After all participants finished the tasks, the testing data were stored into CSV files, which were used as datasets for data mining. The random forest classifier is applied to all these datasets. A stratified 10-fold cross-validation is applied to understand the classifier performance for verification. A 50-percent split validation is then applied for the predictive analysis simulation.

Table 2: Body posture task and instruction

Task Posture	Instruction
Standing	Stand straight Keep gravity center, no foot movement
Sitting	Sit upright, hands on the knees Keep gravity center, no foot movement
Kneeling	Kneel on one kneel (left,right) Keep gravity center, no foot movement
Squatting (Still)	Keep in squat position Keep gravity center, no foot movement
Leaning	Lean on one leg Gravity center shifts to one side, no foot movement
Cross-leg Sitting	Sitting cross-legged (left leg up, right leg up), no foot movement

4.1.2 Result. After conducting data mining on the dataset of 5 test groups, the classifier for body posture identification can reach an average of more than 99% precision following a 10-fold cross-validation. Table 3 shows the statistical results of one test instance of body posture identification by using 10-fold cross-validation. Finally, the accuracy of a 50-percent split validation turned out to be flawless with 100%.

Table 3: Body posture identification test output instance

Total Number of Instances	5636	
Correctly Classified Instances	5635	99.9823%
Incorrectly Classified Instances	1	0.0177%
Kappa statistic	0.9998	
Mean absolute error	0.001	
Root mean squared error	0.0108	
Relative absolute error	0.4384%	
Root relative squared error	3.2804%	

4.1.3 Discussion. The purpose of this test is to verify whether the prototype would be able to body posture by plantar pressure and foot posture. By applying data mining tool to speculate different body postures, the expected identification accuracy exceeded the our expectation. Therefore, it is indicated that a smart shoe may be capable of a flawless body posture identification.

In this test, the body postures are predefined and instructions are provided. However, the actual body postures of participants slightly differed because of their personal habits, but the general postures of the subjects remained the same. When the datasets are obtained, a preliminary analysis was conducted. It has been shown that the variances of the foot acceleration and angular momentum are minuscule. It indicates that participants basically remained still while performing different body postures in the test, which ensures the effectiveness of the datasets. The average plantar pressure distribution of different body postures is very distinctive, resulting in high accuracy for the posture identification. Our result is in line with the preliminary speculation by Matthies et al. [56].

However, in a real-time situation, various sources of noise impact the accuracy while body postures are somewhat different due to personal habits. In future studies, subjects should be able to exhibit a variety of postures without instructions to simulate more realistic situations.

4.2 Ambulation

When people are in different movements, the state of the body parts is different. Meanwhile in our society, people keep paying more attention to their physical conditions. Since, smart wearable devices are progressively advancing, physical condition monitoring is gradually applied in smart wearable devices. Considering foot activity is involved in many movements, we can derive physical body activity, also denotes as ambulation, based on that. We suspect that the plantar pressure and velocity of the foot can show distinctive movement patterns. Therefore, the FSR insole and IMU module should particularly yield important information for detection ambulation activity.

Table 4: Target movement and description

Target movement	Description
Walking	Walking on flat ground Keep a constant speed
Walking uphill	Walk up a slope Keep a constant speed
Walking downhill	Walk down a slope Keep a constant speed
Running	Running on flat ground Keep a constant speed
Go upstairs	Go up the steps Keep a constant speed
Go downstairs	Go down the steps Keep a constant speed
Squatting	Repeatedly squat down and stand up Keep a constant frequency
Jumping	Jump in place Keep a constant frequency

4.2.1 Study Design. In order to structure the dataset, some predefined target movements are ordered as shown in Table 4. The task was executed by a single participant. Each activity was recorded for at least 30 seconds. To ensure the reliability and effectiveness of the study outcome, each recording session was repeated 5 times at different point of times. By applying a sampling rate of 50 Hz, the total instance amount of each movement can reach nearly 7500. In order to reduce the impact of environmental factors, most target movements were conducted on the same type of outdoor ground. The only exception is the testing of going up and down the stairs, which was conducted indoors.

4.2.2 Result. The random forest classifier with 10-fold cross-validation is applied for the data mining and resulted in ~90% precision, while a 50-percentage split showed 84.6% (*see Table 5*).

4.2.3 Discussion. This study revealed the feasibility of using a sensor-packed shoe prototype to distinguish different ambulation movements. In this test, the ambulation movement pattern is trained

Table 5: The output confusion matrix.

a	b	c	d	e	f	g	h	<- classified as
304	0	5	6	15	49	0	2	a = walking
1	**271**	2	2	4	7	0	6	b = running
18	3	**297**	17	32	13	2	13	c = upstairs
14	1	21	**290**	6	26	1	17	d= downstairs
29	5	9	5	**279**	50	2	1	e = uphill
25	1	10	15	30	**488**	0	0	f = downhill
0	0	2	0	0	0	**346**	0	g = squatting
2	0	3	5	0	0	0	**312**	h = jumping

by a single subject only, which yields limitations. Yet, we are unable to determine whether we could build a model that could also work cross-user. However, user-dependent models are suggested for higher accuracy since people show an individual gait. The expected identification accuracy is high, and the final result is in line with the preliminary speculations, such as by Haescher et al. [36] and Pham et al. [72]. By applying the random forest classifier and 50-percent split validation, the weighted average precision is 84.6%, which is similar to the results obtained by previous researchers.

4.3 Gait Identification

A neutral pronation is desirable for the foot to bear the load equally, while overpronation and supination may lead to chronic diseases. The damage to the human body caused by these two kinds of poor gait is introduced in the studies of Naderi et al. [61], Malisoux et al. [51], Pérez-Morcillo et al. [71], and Tweed et al. [84]. Previous research considered the foot-ground-contact pattern and plantar pressure distribution, to identify gait. In our study, we also assume similar sensors to provide sufficiently accurate results for gait identification.

4.3.1 Study Design. Our test data is obtained from a single participant by imitating and excessively exhibiting overpronation and supination (*see Figure 3*). Under the condition of a sampling rate of 50 Hz, the participant walked on a straight road by imitating all three gait styles for 30 seconds. The procedure was repeated five times. After the data was obtained, the data mining was conducted with using conventional machine learning approach deploying a RF classifier.

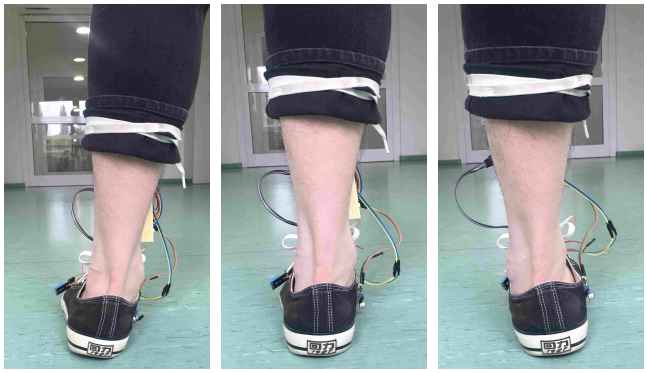

Figure 3: Simulation of three gaits styles: Overpronation (left), Normal (middle), Supination (right)

4.3.2 Result. The 10-fold cross-validation was applied to verify the generalization ability of our model training. As a result, the weighted average precision of gait classification reaches 96.3%. For a predictive analysing, we applied a 50-percent split, which showed a weighted average precision of 95.3%. The confusion matrix of 50-percent split classification is shown in Table 6.

4.3.3 Discussion. The purpose of this test is to identify the capability of potential unhealthy gaits. Both, the 10-fold cross-validation as well as the 50-percentage split suggests the possibility to use a smart shoe for gait identification. Therefore, we can say that a multi-sensory approach can has the capabilities to identify risky gaits. This is also somewhat in line with findings from previous research, such as by Malisoux et al. [51].

Table 6: Confusion matrix for gait identification

a	b	c	<- classified as
706	19	20	a = normal
22	**709**	3	b = overpronation
44	1	**743**	c = supination

However, in our study, the overpronation and supination gaits are exhibited by one subject in a lab setup. During the test, the subject deliberately landed on the outside and inside of the plantar to imitate abnormal gaits. Through this kind of imitation, it is expected that a relatively discriminative result can be obtained, and the final result is in line with the preliminary speculation.

Our short dataset is the biggest catch, which limits us in making any statements regarding the detection of realistically unhealthy gaits. To overcome that, more subjects must be involved to improve the reliability and the predictive power of the result. Besides, the excessive imitation of overpronation and supination that are exhibited by a subject, who has a healthy gait, it is suggested to invite participants that show a naturally unhealthy gait.

4.4 Terrain Identification

When people walk on different terrains, foot posture and movement pattern can be affected. Sand can be hazardous for elderly people to walk because of its instability, while it is suitable for athletes to train because of its high resistance and the property of being relent, thus creating high energy expenditure. Based on the conceptions that terrains exhibit different performance, it may be interesting to identified those. The goal of this study is in understanding, whether we can detect context, such as the terrain using the prototype by using the FSR insole, an IMU module, an MSS module, and a DHT11 sensor. In this study, both the physical characteristics of terrains and movement patterns were considered for the terrain identification.

4.4.1 Study Design. We collected the plantar pressure, motion state, the stepping sound, and the humidity near the ground surface. The test data is obtained from a single participant. In order to obtain sufficient training and test data and to finally ensure the effectiveness of the study, the participant walked on each target terrain for 60 seconds, while wearing the prototype. Considering the data from the MSS module may be affected, the test was conducted in the evening hours at which lower outside noise is present. After the dataset was obtained, the RF classifier is applied for conventional data mining. Again, a 10-fold cross-validation as well as a 50-percent split validation were carried out for verification and predictive analysis.

4.4.2 Results. In order to verify the generalization ability of the RF classifier, the 10-fold cross-validation was firstly applied, which showed a weighted precision for terrain identification of 91.2%. The 50-percent split validation was then applied to verify the possibility of predictive analysis. The confusion matrices are shown in Table 7, and the weighted average classification precision hit 90%. Besides,

the weighted average precision of 50-percent split validation for the wet road identification reached 100%.

Table 7: Confusion matrix for terrain identification.

a	b	c	d	e	f	<- classified as
1481	0	0	0	1	57	a = linoleum
0	**1492**	1	30	21	1	b = lawn
1	59	**1219**	197	4	45	c = tartan
0	8	261	**1219**	32	0	d = pavement
0	2	6	54	**1500**	55	e = sand
37	36	0	0	10	**1358**	f = gravel

4.4.3 Discussion. By utilizing a conventional data mining approach, the weighted average precision exceeds our expectation and indicates that a smart shoe may be capable of detecting terrain one is walking on. This is in line with previous research by Matthies et al. [56]. In a preliminary investigation, we also could confirm that wet surface may be destinguishable from dry surface.

A limitation of this study is the thin dataset, namely the short duration of 60 seconds data per terrain. Although the data may already show differences, realistic accuracy rates are yet to be achieved with mid-long term studies.

Another factor worth looking into is investigating the property of the surface, such as by looking at the insulation (such as by Electric Field Sensing), color (such as by IR/RGB Camera), sound (such as by Ultra/Infra-Sound).

5 LIMITATIONS & OUTLOOK

We would like to outline some further limitations of this research. For now, the monitoring of plantar pressure only relies on three FSRs, which limits the monitoring area and thus precision. The IMU module is tied to the shoe, which may result in some jitter data, and thus, potentially impact the accuracy. The MSS module should only detect the volume of the stepping sound, which may provide inaccuracies if extrinsic noise is present. The humidity of terrains is considered as a separate factor, which may be influenced by the climatic environment. If one would like to make more firm statements on accuracy, a broader dataset with more test subjects are required. As Deep Learning is thriving, it is a choice of technology, once we have sufficient amount of data. Moreover, the prototype is wired, which limits the applicability. In the future, a Bluetooth module can be applied to implement wireless data transmission. Besides, in order to realize the wireless connection, the power supply issue also needs to be solved. Considering this, different working modes should be realized to save energy consumption [31].

As an outlook, the ultimate expectation is to develop a smart shoe that can be user and terrain adaptive. This could provide users with higher protection during walking and running activities. In addition, smart footwear could be used to support monitoring subjects, such as in clinical or field studies (e.g., for rehabilitation purposes). Smart shoes could enable to help ordinary users to change their poor postures, and help patients to recover from injuries or improve poor gait in the future. Further, it has shown that the user's physical condition is often connected to mental state, which is another future direction, which was recently outlined by Elvitigala et al. [29].

6 CONCLUSION

In this paper, we proposed a proof-of-concept shoe that demonstrates the capability of detecting relevant user and context information using a multi-sensory approach. We instrumented a shoe with an accelerometer, a gyroscope, FSRs, a microphone, and a humidity sensor, while we drove a conventional machine learning approach. Our results show that we are capable of extracting information on body posture (e.g., standing, sitting, kneeling, squatting still, leaning, cross-leg sitting) by 100%, ambulation activity (e.g., walking, walking uphill, walking downhill, running, going upstairs, going downstairs, squatting, jumping) by 84.5%, gait abnormalities (e.g., overpronation, supination, normal walking) by 96%, and terrain (e.g., lawn, gravel, sand, tartan, linoleum, pavement) by 91.3%. It is important to note that these accuracy rates mentioned are of theoretical nature and may not translate to the real-world, where substantial noise is present. The evaluation was conducted with 1-5 users, which leaves space for future work. The accuracy provided is of a theoretical nature, as in a real-time application many other influences can impact the data. However, in future, an assistive smart shoe is envisioned to help enable a healthier lifestyle by detecting unhealthy body postures and walking conditions, as well as dangerous behaviors, such as excessive running on unfavourable terrain.

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