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Shoe Based Wearable Sensor

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Abstract— **This article explores how wearable devices combined with machine learning can revolutionize stroke rehabilitation. Wearable devices provide detailed data on patient movements, while ML analyses this data to build models that can improve different areas of rehabilitation. These areas include designing and personalizing training programs, tracking motor recovery with greater accuracy, and enabling remote monitoring outside of clinical settings. However, current methods like constraint induced movement therapy (CIMT) may not be suitable for stroke patients who can't walk independently and have a neurological problem.**

This research builds on previous work to develop a wearable sensor system that monitors a person's activities throughout the day, including different postures and movements. Synchronizing data from both shoes is crucial for the wearable device's main function: objectively comparing how much a person uses their healthy leg versus their affected leg during activities like walking. The devised solution utilized a time-synchronization ping sent by the smartphone every second and reference timestamps derived from the internal timer on each shoe sensor. A time-synchronization ping received by the shoe from the phone provides the initial reference timestamp. Each shoe then reads the sensors every 40ms and increments the timestamp until another ping message is received.

I. Introduction

In recent years, the development of wearable sensor technologies has revolutionized the field of human activity monitoring, offering unprecedented insights into individuals' daily routines and physical behaviours. Among these advancements, shoe-based sensors have emerged as a promising solution for accurately tracking posture allocations and activities in a non-intrusive manner. By integrating sensors directly into footwear, these systems can capture detailed movement data during various activities, providing valuable information for applications such as physical activity management, energy expenditure estimation, and stroke rehabilitation.

The utilization of shoe-based sensors for activity monitoring represents a significant paradigm shift in the way we perceive and analyze human movement. Unlike traditional methods that rely on cumbersome and obtrusive sensor placements on the body, shoe-based sensors offer a more natural and unobtrusive approach, seamlessly integrating into individuals' daily lives without causing discomfort or hindrance. This inherent convenience and ease of use make shoe-based sensor systems well-suited for long-term monitoring in real-world settings, facilitating continuous data collection for comprehensive activity analysis.

One of the key advantages of shoe-based sensor technology lies in its ability to accurately recognize and classify different postures and activities with high precision. By capturing information from patterns of heel acceleration and plantar pressure, these systems can differentiate between weight-bearing and non-weight-bearing activities, such as sitting, standing, walking, jogging, and cycling, with remarkable accuracy. This level of granularity enables researchers and clinicians to gain deep insights into individuals' movement patterns and behaviour, facilitating more personalized and effective interventions for various health and wellness applications.

In this introductory discussion, we delve into the fundamental principles, applications, and challenges associated with shoe-based sensor systems for posture and activity monitoring.

Specifically, we aim to:

- Explore the underlying technology and sensor modalities employed in shoe-based sensor systems.
- Highlight the diverse range of applications and use cases enabled by shoe-based sensor technology, spanning from clinical rehabilitation to sports performance monitoring and everyday activity tracking.
- Discuss the limitations and challenges facing shoe-based sensor systems, including issues related to accuracy, robustness, and user acceptance, and propose potential avenues for future research and development.

By examining the current state-of-the-art and identifying areas for improvement and innovation, this introductory discussion sets the stage for further exploration and advancement of shoe-based sensor technology in the realm of human activity monitoring.
Following this introduction, we will delve into the details of two seminal papers in the field of shoe-based sensor technology for posture and activity monitoring.

Paper 1, titled "Footwear-Based Wearable Sensors for Physical Activity Monitoring," , presents an in-depth exploration of shoe-based sensor technologies and their implications for physical activity management, energy expenditure estimation, and stroke rehabilitation. . In Paper 2, titled "SmartShoe: A Novel Wearable Sensor for Posture and Activity Recognition," we provide an overview of the SmartShoe sensor system, discussing its design, validation results, and potential applications Through these papers, we aim to provide comprehensive insights into the capabilities and limitations of shoe-based sensor systems, shedding light on their role in advancing human activity monitoring technologies.

II. Literature Review 1

Paper 1 introduces a novel wearable sensor system designed to accurately recognize postures and activities using data from heel acceleration and plantar pressure. The study aims to address the limitations of existing activity monitoring devices, which often rely on multiple sensors distributed across the body, leading to inconvenience and obtrusiveness for everyday use.

The sensor system presented in the paper combines data from five force-sensitive resistors (FSRs) integrated into the insole of the shoe and a 3-D accelerometer positioned on the back of the shoe. This setup allows for the collection of data related to heel strike, stance phase, toe-off, and motion trajectory, enabling the characterization of various postures and activities.

The study involves testing the sensor system on nine adult subjects performing a range of activities, including sitting, standing, walking, running, stair ascent/descent, and cycling. Support Vector Machines (SVMs) are employed for classification, with a focus on achieving high accuracy while minimizing preprocessing and feature extraction requirements.

Data collection procedure:

The data collection procedure involved nine adult subjects (three males and six females) wearing the sensor-equipped shoes during a single visit lasting 2.5-3 hours. Subjects were healthy, non-smokers, with stable weight over the previous six months and were sedentary to moderately active. Pregnant women and individuals with impairments preventing physical activity were excluded. The subjects' ages ranged from 18 to 21 years, with body mass index (BMI) ranging from 18.1 to 39.4 kg/m² and shoe sizes (US) ranging from 9.5-11 for men and 7-9 for women.

TABLE I
DATA COLLECTION PROTOCOL

Stage	Description
1	Sit/Stand motionless
2	Walking/Jogging on treadmill: 6 minute trials, 5 minute rest between trials. Four level trials: 2.4 km/h (1.5 mph) 4.0 km/h (2.5 mph) 5.6 km/h (3.5 mph) 7.2 km/h (4.5 mph)
3	Ascend/Descend stairs – 6 of each
4	Sit/Stand (with fidgeting)
5	Walking on treadmill: 6 minute trials, 5 minute rest between trials Walking on sloped surface: 4.0 km/h at ± 1.5% grade Loaded trial carrying 10% of body weight
6	Cycling: 50W, 50 rpm 100W, 75rpm

The data collection protocol is shown in Table I. A total of 11 h 36 min of data were recorded for six major posture/activity classes:

1) class “sitting” (which includes sitting motionless and with fidgeting, total time 1 h 47 min)

2) class “standing” (includes standing motionless and with fidgeting, 1 h 47 min)
3) class “walking/jogging” (includes all speeds, slopes, and load conditions, 5 h 57 min)

4) class “ascending stairs” (18 min)

5) class “descending stairs” (17 min); and 6) class “cycling” (includes 50 and 75 r/min, 1 h 30 min)

All data were used in the analysis and approximately equally distributed across subjects.

Findings:

1. **High Accuracy Classification:** The sensor system demonstrates impressive accuracy in classifying postures and activities, with an average accuracy of 95.2% on the full sensor set and over 98% on an optimized sensor set. This accuracy is maintained even with a significant reduction in sampling frequency, indicating robust performance.
2. **Usability Across Population:** The device shows promise for use across individuals with varying anthropometric characteristics, as subjects had diverse shoe sizes (US M9.5-11 and W7-9) and body mass index (BMI) ranging from 18.1 to 39.4 kg/m².
3. **Minimal Preprocessing Requirement:** The sensor system requires minimal preprocessing, with no need for complex feature extraction algorithms. This simplifies data analysis and reduces computational burden, enhancing practicality for real-world applications.
4. **Energy Efficiency:** The study demonstrates the ability to reduce sampling frequency without significant loss of accuracy, leading to reduced power consumption for wireless transmission. This energy efficiency is crucial for prolonged use and practical implementation in wearable devices.
5. **Validation of Methodology:** The methodology is rigorously validated through various experiments, including individual and group models, investigation of sensor configurations, sensitivity to sampling frequency, and comparison between one and two shoe configurations. These experiments provide robust evidence of the effectiveness and versatility of the proposed sensor system.

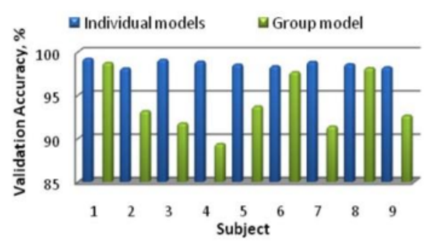


Fig. 2. Average validation accuracy in six-class recognition for each subject. The group model included data from all sensors.

Predicted class

Actual class	Sit	Stand	Walk Jog	Ascend	Descend	Cycle	**Class-specific recall**
Sit	*3202*	*2*	*0*	*0*	*0*	*14*	**0.99**
Stand	*7*	*3191*	*2*	*7*	*0*	*0*	**0.99**
Walk	*0*	*0*	*10647*	*74*	*0*	*0*	**0.99**
Ascend	*0*	*0*	*34*	*500*	*15*	*1*	**0.90**
Descend	*0*	*0*	*41*	*60*	*405*	*0*	**0.80**
Cycle	*146*	*3*	*0*	*0*	*0*	*2539*	**0.94**
Class-specific precision	**0.95**	**1.00**	**0.99**	**0.78**	**0.96**	**0.99**	**0.98**

Fig. 4. Population-cumulative confusion matrix, showing classification accuracy for the best sensor configuration in the group model. Numbers in italic show the quantity of 2-s epochs for each class. Class-specific recall is the proportion of a class instances that were correctly identified. It is defined as a ratio of the respective diagonal value to the sum of a row. Class-specific precision is the proportion of the predicted class cases that were correct. It is defined as a ratio of the corresponding diagonal value to the sum of a column. This model was obtained using the following sensors: $A_{AP}, A_{ML}, A_{SI}, P_H, P_{1M}, P_{HX}$.

While the wearable sensor system presents promising capabilities, several limitations must be acknowledged and addressed to enhance its practical utility and reliability.

1. **Limited Scope:** Focuses primarily on recognition of common postures and activities, potentially lacking specificity for specialized activities.
2. **Single Modality:** Relies on a combination of heel acceleration and plantar pressure, which may not capture all nuances of complex movements.
3. **Dependency on Footwear:** Requires individuals to wear sensor-equipped shoes, limiting application in scenarios where footwear is not worn.
4. **Durability Concerns:** Traces on some shoes may fail under high forces during certain activities, indicating potential durability issues that need addressing.
5. **Generalization:** While effective in controlled settings, generalization to real-world conditions may require further validation and testing.

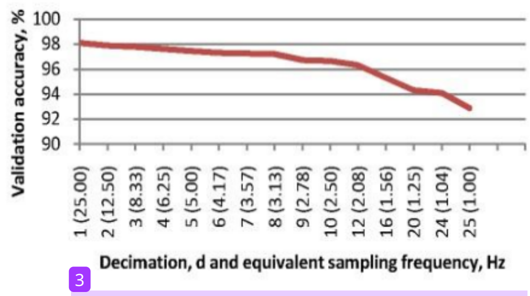


Fig. effectively demonstrates tolerance of the proposed combination of sensor modalities to lower sampling frequencies. While the highest accuracy of 98.1% is observed at 25 Hz, the relative decline for 5 Hz sampling is only 0.6% (accuracy of 97.5%). As an example, [14] reported a relative decline of 12% (from 85% to 75%) while changing sampling from 25 to 5 Hz for Y -axis of an accelerometer. This useful property allows for lower data rates in a body network and a potential for extended battery life.

III. Literature Review 2

The paper discusses the development and application of SmartShoe, a novel wearable footwear sensor system for monitoring physical activity (PA), energy expenditure (EE), and gait. The SmartShoe utilizes a combination of a 3D accelerometer and pressure sensors embedded in the insole of conventional footwear to accurately recognize common postures and activities while minimizing intrusiveness to the wearer. The system aims to address the limitations of existing devices, which often rely on multiple sensors distributed on the body and may be too obtrusive for everyday use.

Fig. 1. SmartShoe device: (a) Overall view of the shoe device with attached accelerometer, battery and power switch on the back; (b) Pressure-sensitive insole with 5 pressure sensors: heel (1), 3rd metatarsal head (2), 1st metatarsal head (3), 5th metatarsal head (4), hallux (5); (c) The wireless electronics board

Data collection procedure:

Two human studies were conducted to develop and validate the SmartShoe system. In the first study (HS1), data was collected from 16 healthy individuals performing various postures and activities while wearing SmartShoe and a portable metabolic mask system. These activities included sitting, standing, walking, jogging, stair ascent/descent, and cycling. Metabolic data were collected to estimate energy expenditure, and participants also walked over a GAITRite® system to measure gait parameters

Table 1. Subject characteristics of HS1

	Men (N=8)		Women (N=8)	
	Mean ± SD	Range	**Mean ± SD**	Range
Weight, kg	86.8 ± 20.0	59.0-119.8	66.9 ± 16.8	48.6-100.9
Height, in.	69.3 ± 1.8	67.0-72.0	64.3 ± 2.8	61.0-70.0
BMI, kg·m^{-2}	28.0 ± 5.9	18.9-35.8	25.4 ± 7.3	18.1-39.4
Age, yr	25.6 ± 8.6	18-44	24.4 ± 3.9	18-29
Shoe size, US	10.3 ± 0.6	9.5-11.0	7.9 ± 0.7	7.0-9.0

The second study (HS2) involved subjects post-stroke, where data was collected to assess the system's performance in monitoring sitting, standing, and walking postures. Subjects performed these activities while wearing SmartShoe and were evaluated using clinical tests to assess motor and mobility function.

Table 3. Subject characteristics of HS2

Age (years)	60.1 (9.9)
Time since stroke (months)	51.7 (45.1)
Berg Balance Scale	44.3 (11.7)
Fugl Meyer LE motor score	25.8 (5.9)
Self-selected gait speed (m/s)	0.69 (0.35)
Stroke Impact Scale 16	65.4 (22.0)
Mini Mental State Exam	28.7 (2.1)
Ankle Foot Orthotic Use (yes:no)	2:6

Since ,it is capable of differentiating between weight-bearing and non-weight bearing activities, SmartShoe is capable of accurate energy expenditure estimation by reducing prediction error in sedentary postures (for example, sitting vs standing) and some activities (walking/jogging vs cycling). Presented below is a methodology for estimating EE of healthy individuals from HS1. The EE estimation model was constructed as a group model: the data used for training were pooled from several subjects and such model was then tested on the validation set which included data from subject(s) that were not in the training set.

The EE model was by branched activity ("Sit", "Stand", "Walk", "Cycle") where activity prediction was performed using the SVM classifier from Section 4 and each activity (branch) had its own regression for predicting EE (Figure 6). To match time resolution of the system used measure EE during the experiments, EE estimation was based on the sensor data collected during 1 minute intervals in which subjects were in metabolic steady state (minutes 4-6 of each trial of HS1). Each one minute recording resulted in approximately 1500 (25Hz· 60s) points of pressure and acceleration data per channel. For the 16 subjects who participated in the study there were a total of 208 such recordings.

Findings:

1. Posture and Activity Classification:

- The SmartShoe system achieved high accuracy rates in classifying various postures and activities for both healthy individuals and those post-stroke.

- Average accuracy rates ranged from 95% to 98%, indicating the system's ability to differentiate between activities such as sitting, standing, walking, jogging, stair ascent/descent, and cycling.
- These results suggest that SmartShoe can reliably recognize a wide range of postures and activities commonly encountered in daily life.

2. Energy Expenditure Prediction:

- The system demonstrated accurate prediction of energy expenditure, with a root-mean-square error (RMSE) of 0.69 METs.
- This level of accuracy indicates the system's capability to estimate energy expenditure during various activities, providing valuable insights for obesity research and weight management programs.

3. Temporal Gait Parameters:

- SmartShoe reliably identified temporal gait parameters, such as cadence, step time, cycle time, and percentages of gait cycle phases (swing, stance, single limb support, double limb support) for each lower extremity.
- Statistical analyses showed no significant differences between gait parameters estimated by SmartShoe and those measured by a commercial gait measurement system (GAITRite®).
- These findings suggest that SmartShoe can accurately assess gait characteristics, which is crucial for monitoring motor recovery after stroke and evaluating the effectiveness of rehabilitation interventions.

4. Comparison with Previous Studies:

- SmartShoe's performance surpassed or matched that of previous studies utilizing similar methodologies or sensor systems.
- Compared to single-location methodologies or accelerometer-based sensors, SmartShoe demonstrated higher accuracy rates in recognizing postures, activities, and gait parameters.
- The system's ability to achieve accurate results across different populations, including healthy individuals and those with neurological disorders, highlights its robustness and versatility.

5. Validation and Reliability:

- The findings from both human studies (HS1 and HS2) support the validity and reliability of SmartShoe for monitoring physical activity, energy expenditure, and gait in real-world settings.
- Validation procedures, including statistical analyses and comparison with established measurement systems, confirmed the accuracy and consistency of SmartShoe's measurements.
- These results provide confidence in the system's utility for various research and clinical applications, indicating its potential to improve the assessment and management of physical activity and mobility in diverse populations.

Overall, the detailed findings underscore the effectiveness of SmartShoe as a wearable sensor system for comprehensive monitoring of physical activity, energy expenditure, and gait, with implications for obesity research, stroke rehabilitation, and other clinical applications.

Predicted class

Actual class	Sit	Stand	Walk Jog	Ascend	Descend	Cycle	Class-specific recall
Sit	*3202*	*2*	*0*	*0*	*0*	*14*	**0.99**
Stand	*7*	*3191*	*2*	*7*	*0*	*0*	**0.99**
Walk/Jog	*0*	*0*	*10647*	*74*	*0*	*0*	**0.99**
Ascend	*0*	*0*	*34*	*500*	*15*	*1*	**0.90**
Descend	*0*	*0*	*41*	*60*	*405*	*0*	**0.80**
Cycle	*146*	*3*	*0*	*0*	*0*	*2539*	**0.94**
Class-specific precision	**0.95**	**1.00**	**0.99**	**0.78**	**0.96**	**0.99**	**0.98**

Fig. 3. Population-cumulative confusion matrix showing classification accuracy for the best sensor configuration { A_{AP}, A_{ML}, A_{SI}, P_H, P_{MI}, P_{HX} } for healthy individuals in HS1. Numbers in italic show the quantity of 2-second time intervals for each class. Class-specific recall is the proportion of a class instances that were correctly identified. It is defined as a ratio of the respective diagonal value to the sum of a row. Class-specific precision is the proportion of the predicted class cases that were correct. It is defined as a ratio of the corresponding diagonal value to the sum of a column.

Innovative advancements in wearable sensor technology have revolutionized the monitoring of physical activity, energy expenditure, and gait, offering promising solutions for diverse applications in healthcare and research. However, despite its numerous benefits, the system is not without limitations, as outlined below.

1. Cost Considerations: The implementation of SmartShoe technology may incur significant costs, including the development of sensor-equipped footwear, data processing algorithms, and integration with compatible devices or platforms. This expense could limit its accessibility for

research institutions or healthcare facilities with budget constraints.

2. User Comfort and Compliance: While SmartShoe aims to be minimally intrusive, individuals may experience discomfort or reluctance to wear sensor-equipped footwear regularly, especially during extended periods or in diverse environmental conditions. Poor user compliance could undermine data quality and reliability, affecting the system's overall effectiveness.

3. Privacy Concerns: Continuous monitoring of physical activity and gait using wearable sensors raises privacy considerations related to data security and confidentiality. The collection and storage of sensitive personal health information could expose users to privacy breaches or unauthorized access, necessitating robust privacy safeguards and compliance with regulatory requirements.

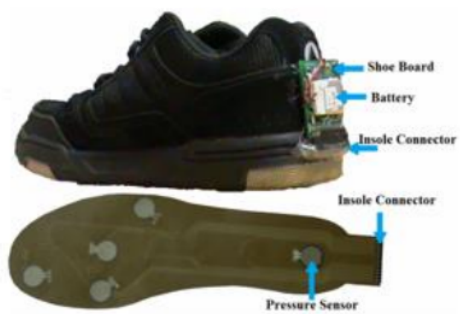
4. Interference with Natural Movements: The placement of sensors within footwear may alter the natural biomechanics of walking or running, potentially affecting gait patterns or posture dynamics. This interference could introduce biases or inaccuracies in activity classification and energy expenditure estimation, particularly for individuals with pre-existing musculoskeletal conditions or gait abnormalities.

5. Limited Customization: SmartShoe's classification models and algorithms may lack customization options for different user populations, such as children, elderly individuals, or individuals with specific medical conditions. This one-size-fits-all approach may overlook unique movement patterns or activity behaviors, compromising the system's accuracy and relevance for diverse user demographics.

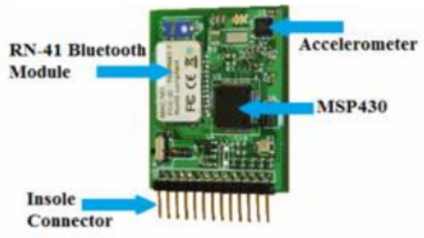
These drawbacks highlight the need for ongoing refinement and adaptation of SmartShoe technology to address user needs, technological challenges, and ethical considerations in the field of wearable sensor-based monitoring.

IV. LITERATURE REVIEW 3

This system uses pressure insoles and accelerometers embedded in a pair of shoes to collect data on a person's activity throughout the day. The data, including pressure and acceleration measurements, is captured at a rate of 25 times per second and transmitted wirelessly to a base computer using WISAN technology. In the future, the system aims to compare data from both shoes to analyze how much a person uses their affected leg compared to the healthy one. To achieve everyday usability, the design is transitioning from a lab-based system to a wearable one. This wearable system utilizes a smartphone as a portable "base station" for data collection and potentially future processing. Bluetooth technology is chosen for communication between the smartphone and the shoe sensors due to its widespread use and user familiarity.



The design of the shoe sensor prioritized low power consumption and a small footprint to ensure comfortable everyday use. Each shoe sensor incorporates a microcontroller, Bluetooth module, and accelerometer. The TI MSP430F2417 microcontroller was selected for its low power features. Bluetooth was chosen for data transmission due to its compact size and compatibility with many devices. To further reduce size and power usage, the system also includes a low-power accelerometer and power management circuitry. The final product is a lightweight sensor (15 grams) that doesn't hinder movement. It consumes only 40mA while collecting data and can operate for 12 hours on a single 500mAh battery.



(a) (b)

Fig. 3 Smartphone visualization of data. (a) Pressure Sensor Dashboard, (b) Accelerometer Graphs

Fig. 4. The smartphone and shoes communication routine over Bluetooth.

Methods:

1. **Bluetooth Communication Link Tests/Asynchronicity Testing**:
   - First two tests focused on the Bluetooth communication link.
   - Investigated the asynchronicity of ping messages received between the shoes.
   - The phone sent a ping message to the sensors every one second.
   - The oscilloscope measured the difference in ping message reception times between the left and right shoes.
2. **Sample Validation/Long-Term Synchronization Testing**:
   - Ensured that samples paired together on the phone corresponded to the same sample period.
   - Used a function generator to provide a perfectly synchronized input (0.05Hz triangle wave) to both heel sensors.
   - Expected two perfectly synchronized output waveforms—one from each shoe.
   - Maximum and minimum readings should align in the data produced by the phone.
   - Experiment conducted over a 5-hour period.
3. **Compatibility Test**:
   - Verified compatibility of th e proposed wearable platform with a previously used laboratory system.
   - Specifically tested compatibility with a posture and activity classification model.
   - Small study with three participants:
     - Participants wore the device and collected one hour of data.
     - Required to stand, walk, and sit for twenty minutes each.
     - Data classified using a support vector machine trained with tsudihe original system.

Findings:

1. **Asynchronicity Testing**:
   - Longest difference in arrival of ping messages: **24 ms**.
   - Most common time differences between sensors receiving ping messages: **4 ms** or **8 ms**.

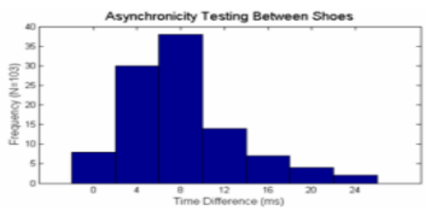


Fig. 5. Asynchronicity between the left and right shoes.

2. **Long-Term Synchronization Testing**:
   - Smartphone received a triangle wave during the 5-hour test period.
   - Visual inspection showed continuous synchronization as left and right shoe waveforms overlapped.
   - Computational verification:
     - Compared maximum and minimum readings between shoes.
     - **62%** of the time, synchronization was exact.
     - **99%** of the time, synchronization was within one sample.
3. **Small-Scale Study Results**:
   - Recognition of postures and activities using the new system: **over 99%** accuracy.
   - Confusion matrix (Table I) combined results for all three participants.
   - Classifier from [13] classified activities as:
     - **Sitting**
     - **Standing**
     - **Walking**
     - **Ascending steps**
     - **Descending steps**
   - For this study, **walking**, **ascending steps**, and **descending steps** were grouped together as **walking**.

		Predicted class			
		Sit	Stand	Walk	Class-specific recall
Actual class	Sit	1928	0	0	1.000
	Stand	9	1964	10	0.990
	Walk	0	0	2028	1.000
	Class-specific precision	0.995	1.000	0.995	**0.9968**

Pros:

- **Minimal obstruction:** The shoe sensors are lightweight and comfortable for daily wear.
- **Data collection and processing:** The system allows for data collection throughout daily activities.
- **Smartphone compatibility:** The smartphone "base station" is portable and offers long-term data storage.
- **Potential for on-device processing:** Modern smartphones may be powerful enough for future analysis directly on the device.
- **Accurate synchronization:** Testing shows minimal time difference between shoe sensors (within acceptable range for accurate data comparison).

- **Compatibility with lab system:** Data collected by the wearable system is compatible with the lab system for posture and activity recognition, even though different accelerometer models were used.
- **High accuracy:** The wearable system achieves high accuracy in recognizing postures and activities.

Cons:

- **No current on-device processing:** The system currently relies on a smartphone for data processing, potentially limiting usability in situations without a phone.

V. Methodology Report

The goal of the project is to create and assess a wearable sensor system for stroke recovery. This method gathers information about an individual's every day activities by using accelerometers and pressure insoles that are implanted in a pair of shoes. Using WISAN technology, the gathered data—which includes pressure and acceleration measurements—are wirelessly sent to a base computer. Each of the three broad categories of experimental techniques used in the study supports a proponent of this paradigm. The advantages include low obstruction, ongoing data collection, smartphone compatibility, accurate synchronization, interoperability with lab systems, the possibility of on-device processing, and excellent activity detection accuracy. However, there are some drawbacks as well, such as the dependence on smartphones for data processing, which may restrict usability in situations where a phone is not present.

Device Components and Design Considerations:

- Pressure insoles and accelerometers for activity data collection.
- Microcontroller (TI MSP430F2417), Bluetooth module, and low-power accelerometer in each shoe sensor.
- Bluetooth communication with a smartphone acting as a portable "base station."
- Power management circuitry to ensure low power consumption and extended battery life (12 hours on a single 500mAh battery).

Experimental Methods:

Bluetooth Communication Link Tests / Asynchronicity Testing:

- Conducted tests to evaluate the Bluetooth communication link between the smartphone and shoe sensors.
- Investigated the asynchronicity of ping messages received by the left and right shoes.
- Utilized an oscilloscope to measure the time differences in ping message reception.
- The phone sent ping messages every second to synchronize data collection.

Sample Validation/Long-Term Synchronization Testing:

- Validated samples paired together on the phone to ensure synchronization.
- Used a function generator to provide synchronized input to both heel sensors.
- Expected perfectly synchronized output waveforms from each shoe.
- Conducted a 5-hour test period to assess long-term synchronization.

Compatibility Test:

- Verified the compatibility of the wearable platform with a previously used laboratory system.
- Tested compatibility with a posture and activity classification model using a small study with three participants.

- Participants wore the device and performed specific activities for data collection and classification.

Limitations:

- Limited Scope: Focuses primarily on recognition of common postures and activities, potentially lacking specificity for specialized activities.
- Single Modality: This relies on a combination of heel acceleration and plantar pressure, which may not capture all nuances of complex movements.
- Dependency on Footwear: Requires individuals to wear sensor-equipped shoes, limiting application in scenarios where footwear is not worn.
- Durability Concerns: Traces on some shoes may fail under high forces during certain activities, indicating potential durability issues that need addressing.
- Generalization: While effective in controlled settings, generalization to real-world conditions may require further validation and testing

VI. CONCLUSION

In conclusion, the emergence of shoe-based sensor technologies has brought about a significant transformation in human health activity monitoring. These designs offer a non-invasive, convenient and reliable method for tracking postures and body activity. Integration of these monitoring sensors into footwear ensures these systems naturally blend into daily life, enabling long term monitoring without discomfort and inconvenience.

However, despite the promising capabilities of shoe-based sensor technology, several challenges and limitations remain to be addressed. These include cost considerations, privacy concerns, and potential interference with natural movements of the person. Future efforts are required to refine these systems to meet user standards, technological challenges, and ethical/privacy concerns.

Advancements in wearable sensor technology, such as smartphone compatible wearable systems offer avenues for further enhancing the usability and effectiveness of shoe-based sensor technology in monitoring gait, physical activity, and energy expenditure, thus paving the way for more innovation and advancement in this field.

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