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A SMART INSOLE SYSTEM INTEGRATED WITH HEIGHT PARAMETER TO IMPROVE THE PERFORMANCE OF AN ATHLETE

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Abstract
This paper is aimed to access the validity of an instrumented insole system for measuring spatiotemporal parameters during running. This spatio temporal parameters include stride time, ground contact time, swing time and step frequency were collected across various running conditions. Gathering of the parameter data is called Gait analysis. This analysis plays a major role in optimizing athletic performance, rehabilitation, medical condition etc. Even though it performs a major role in our project it also has some drawbacks and limitations. High quality Gait equipment such as motion capture system and force plates can be very expensive to purchase and maintain. Conducting gait analysis often requires specialized facilities or laboratories. Gait can vary between individuals and also the same individual on different days. Previous shoe insole projects focused on only improving running technique, but in our project we are going to add a new parameter that is height which is used for measuring the distance between ground contact and raised foot. This can be implemented in athletics like high jump, hurdles etc. Sensors are devices that pick up physical quantities and respond to them. Their use has grown exponentially, and for certain people they are an essential part of their daily life. The main purpose of the proposed system was to develop a prototype for a shoe which would allow us to gather detailed information on each step taken by a person. The reason for the development of this product was to obtain a more accurate number about the steps a person takes, and at the same time, monitor those steps, with the objective of preventing injuries or correcting habits. To prepare the case, a study and analysis of the market was carried out on the different devices that resembled the objective of the system. Then, an analysis was made to determine which hardware was necessary to make a prototype. After that, a study on which programming style (native vs hybrid) to use was made. An analysis of their possible development and different problems that can lead to the product development process is

discussed. A study of the several hardware components is carried out. Also, a basic multiplatform app is developed to check the BLE connectivity and receive the information provided by the hardware. Sensors are essential devices that detect physical quantities and have become integral in people's daily lives.
Keywords- Gait Analysis , Spatiotemporal parameters , Biomechanical Analysis

1 Introduction

As the years go by, technology advances, and it does not do it gradually; it does it exponentially to satisfy the needs of its consumers, us.

Running is a ubiquitous physical activity with extensive health and performance implications, making it a subject of considerable interest in the fields of sports science and biomechanics. Understanding the intricate mechanics of running not only contributes to athletic performance optimization but also holds significant implications for injury prevention and rehabilitation. In recent years, advancements in wearable technology have offered promising avenues for real-time monitoring of running biomechanics, ushering in a new era of data-driven insights into the sport.

One such innovation in this realm is the insole system, which combines pressure sensors with advanced algorithms to capture spatiotemporal parameters and biomechanical data during running. These insoles have gained attention for their potential to provide athletes, coaches, and researchers with an accessible and portable tool for analyzing running gait and performance metrics. However, before widespread adoption in sports and clinical applications, it is imperative to rigorously evaluate the accuracy and validity of these wearable system. This research project undertakes the vital task of assessing the insoles' performance as a wearable system for monitoring spatiotemporal parameters and biomechanics during running. The project's objectives encompass various facets, including the evaluation of spatiotemporal parameters such as ground contact time, flight time, stride time, and step frequency and height parameter. Additionally, the study examines the potential presence of sensor drift in the wearable technology. Through rigorous statistical analyses, such as mean absolute percent error calculations.

One of the most outstanding devices that has been implemented both for professional and domestic use are the sensors. We live surrounded by sensors, working and helping to make our life much easier, for example by turning the lights on or off with a clap, detecting our presence, temperature, air pressure, humidity, speed or even detecting how much we have left in our vehicle.

Sensors are devices that can capture physical data, quantities, or other alterations of its surroundings . They are used to develop smart devices such as smart insole in shoes, or smart home devices, et cetera. These sensors can change or simplify our daily lives in an incredible way. The examples mentioned above are just a small sample of the different types of sensors that exist. One of the fields where the use of sensors can be highlighted is the sports and health field. In the sport field, with the use of sensors, the range of information received can be increased, allowing an improvement both I nutrition and

physical activity. Also, in the health field, sensors can detect the heart rate of a patient to keep him under control. For example, by obtaining data on how a person walks, you can see if there are any problems walking.

Even by counting the number of steps, you can calculate the amount of physical movement that a person is doing during the day. Health and sports are examples of fields where sensors have provided a great technological contribution. Most of the computer systems that make use of sensors are real-time systems. It is a type of system that must give a valid response within a range of time to an event that has been generated. This event belongs to the environment in which the real- time system is operating. Systems like robots or a weapon firing control system are examples of real-time systems

2 Scope

The scope of this project is a scientific research study aimed at accessing the validity and accuracy of the insoles as a wearable system for monitoring spatiotemporal parameters and biomechanics during running and jumping. Our instruments are equipped with pressure sensor, and captures motion and measures Ground reaction. These insoles can be used in day to day activities, prevents injury, rehabilitation and optimizes athletic performance.

This project is aimed to access the validity of an instrumented insole system for measuring spatiotemporal parameters during running. These spatiotemporal parameters include stride time, ground contact time, swing time and step frequency were collected across various running conditions.

Running biomechanics analysis is fundamental to sports science, athletic training, and injury prevention. Accurate and reliable measurement of spatiotemporal parameters during running, such as ground contact time and step frequency, plays a crucial role in understanding and enhancing athletic performance. While traditional measurement methods are often cumbersome and costly, wearable technology presents a potential solution for convenient and portable data collection.

Addressing this problem requires a comprehensive evaluation of the accuracy, validity, and reliability of our insoles, considering both traditional running biomechanics and the specific demands of high jump analysis. The inclusion of the height parameter adds an additional layer of complexity and significance to the project's objectives.

3 Relevant Works

[1] N. Ivanov. (2019). Unleashing the Internet of Things With In-Memory Computing—IoT Now—How to Run an IoT Enabled Business. Accessed: Jul. 7, 2021. [Online]. Available: https://www.IoT-now.com/2019/01/17/92200-unleashing-internet-things-memory computing.

A modern in-memory computing (IMC) platform brings together multiple IMC capabilities into a unified experience to simplify deployment and management.

[2] S. C. Mukhopadhyay and N. K. Suryadevara, ''Internet of Things: Challenges andopportunities,'' in Internet of Things. Springer, 2014, pp. 1–17, doi: 10.1007/978-3-319-04223-7_1. t The term Internet of things (IoT) is used to describe embedded devices (things) with Internet connectivitsy, allowing them to interact with each other, services, and people on a global scale. This level of connectivity can increase reliability, sustainability, and efficiency by improved access to information. Environmental monitoring, home and building automation and smart grids could be interconnected, allowing information to be shared between systems that affect each other. Giving these systems better awareness can improve their efficiency, reliability and sustainability. Due to the large number of applications the IoT has the potential to replace people as the largest consumer and producer of information on the Internet.

[3] F. Saeik, M. Avgeris, D. Spatharakis, N. Santi, D. DechounIoTis, J. Violos, A. Leivadeas, N. Athanasopoulos, N. Mitton, and S. Papavassiliou, ''Task offloading in edge and cloud computing: A survey on mathematical, artificial intelligence and control theory solutions,'' In this paper, we have presented a detailed and comprehensive study of the task offloading problem and we have extensively analyzed the main components and different computing paradigms of an end-to-end communication path. This path starts at the end device (i.e., mobile/IoT devices) and leverages the benefits of the added computational resources at the edge of the network, before ending up to the Cloud.

[4] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, ''A survey on mobile edgecomputing: The communication perspective,''.Driven by the visions of Internet of Things and 5G communications, recent years have seen a paradigm shift in mobile computing, from the centralized mobile cloud computing toward mobile edge computing (MEC). The main feature of MEC is to push mobile computing, network control and storage to the network edges (e.g., base stations and access points) so as to enable computation-intensive and latency-critical applications at the resource-limited mobile devices. MEC promises dramatic reduction in latency and mobile energy consumption, tackling the key challenges for materializing 5G vision.

[5] D. DechounIoTis, N. Athanasopoulos, A. Leivadeas, N. Mitton, R. Jungers, and S. Papavassiliou, ''Edge computing resource allocation for dynamic networks: The DRUID-NET vision and perspective,'' Sensors, vol. 20, no. 8, p. 2191, Apr. 2020, doi: 10.3390/s20082191. This article presents the most important challenges of IoT-enabled applications, along with the perspective and the basic concepts and objectives of the novel DRUID-NET framework.

[6] Q. Xu, R. Zheng, W. Saad, and Z. Han, ''Device fingerprinting in wireless networks:Challenges and opportunities,'' IEEE Commun. Surveys Tuts., vol. 18, no. 1, pp. 94–104, 1sQuart., 2016, doi: 10.1109/COMST.2015.2476338. Node forgery or impersonation, in which legitimate cryptographic credentials are captured by an adversary, constitutes one major

security threat facing wireless networks. The fact that mobile devices are prone to be compromised and reverse engineered significantly increases the risk of such attacks in which adversaries can obtain secret keys on trusted nodes and impersonate the legitimate node. One promising approach toward thwarting these attacks is through the extraction of unique fingerprints that can provide a reliable and robust means for device identification.

[7] O. N. Osterbo, D. Zucchetto, K. Mahmood, A. Zanella, and O. Grondalen, ‘‘State modulated traffic models for machine type communications,’’ in Proc. 29th Int. Teletraffic Congr. (ITC), Ilmenau, Germany, Sep. 2017, pp. 1–5.

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4. Existing System

Smart insoles refer to insoles equipped with technology that can track various metrics related to foot health, activity, or performance. While the specifics of these systems can vary, here are some common features found in existing smart insole systems:

1. Pressure Sensors: Smart insoles often include pressure sensors to monitor how pressure is distributed across the foot. This information is valuable for gait analysis, identifying pressure points, and preventing foot problems.
2. Motion Sensors: Inertial motion sensors (like accelerometers and gyroscopes) are used to detect movement and orientation. This can help in tracking steps, recognizing specific activities, and analyzing posture.
3. Bluetooth Connectivity: Many smart insoles connect to smartphones or other devices via Bluetooth. This allows for real-time data transfer and analysis, and often provides the user with a mobile app to view their data.
4. Foot Health Monitoring: Some smart insoles are designed to monitor foot health, tracking changes in temperature, moisture, or even detecting issues like diabetic foot ulcers.

5. Activity Tracking: Smart insoles can count steps, measure distance, and even provide data on the quality of a workout, helping athletes and fitness enthusiasts monitor their performance.
6. Feedback and Alerts: Users can receive feedback through mobile apps or even insoles with built-in haptic feedback. This can include posture correction alerts, reminders to change shoe inserts, or notifications about potential foot problems.
7. Customization: Certain systems allow for customization, like selecting different types of insoles (e.g., for running, walking, or standing) and adjusting sensitivity settings.
8. Medical and Therapeutic Applications: Some smart insoles are designed for medical purposes, like monitoring the gait of patients recovering from injuries or surgery.
9. Data Analysis: These systems often provide data analytics, helping users and healthcare professionals make informed decisions about foot health and performance
10. Integration: Many smart insole systems are designed to work with other wearable devices, like fitness trackers or smartwatches, for a more comprehensive overview of health and activity.

The specific features and capabilities can vary between different smart insole brands and models, and new advancements in technology continue to expand the capabilities of these devices.

5. Proposed System

We are attempting to include a parameter named height in the proposed work, which tracks the height in both static and motion. Here, height is referred to as the distance from the ground to the floor at the foot. In the initial stage, we'll just connect the shoe to measure the height. If this is successful, we'll mix it even more with the current model. This allows us to combine pressure, angle, and height to create a composite for gait analysis.

Certainly, including a parameter like "height" in your proposed work for smart insoles can have significant implications for gait analysis and other applications. Here's an expanded explanation:

Smart insoles are increasingly being developed to provide a comprehensive understanding of foot health, posture, and movement. In this context, the parameter "height" refers to the distance from the ground to the floor at the location of the foot. By integrating this measurement into the smart insole system, you are aiming to add an essential dimension to the data collected.

In the initial stage, your focus is on connecting this "height" measurement to the shoe. This connection will enable the insole to capture both static and motion-related changes in height. For instance, during static measurements, it can help in identifying subtle variations in foot arch height or uneven pressure distribution while standing still. During motion, it becomes invaluable in tracking fluctuations in height as the foot lifts, moves, and strikes the ground during walking, running, or other activities.

The successful integration of the "height" parameter into the smart insole system opens up a world of possibilities for further enhancement. You can combine this data with existing features such as pressure sensors, which reveal how force is distributed across the foot, and motion sensors, which detect movement and orientation. The addition of "height" creates a composite dataset that is incredibly valuable for gait analysis.

Gait analysis, the study of human walking patterns, relies on a holistic understanding of how the foot interacts with the ground. By combining pressure, angle, and height data, you can gain deeper insights into not only the pressure points and foot positioning during each step but also how the height of the foot changes throughout the gait cycle. This information is crucial for assessing gait abnormalities, identifying biomechanical issues, and tailoring interventions for individuals, whether for rehabilitation, sports performance optimization, or general foot health. In summary, the integration of the "height" parameter into smart insoles represents a promising advancement in the field of wearable technology. It has the potential to significantly improve the accuracy and scope of gait analysis, contributing to a more comprehensive understanding of foot health and movement dynamics. Success in this endeavor may pave the way for innovative applications in healthcare, sports, and beyond.

Work Flow Diagram

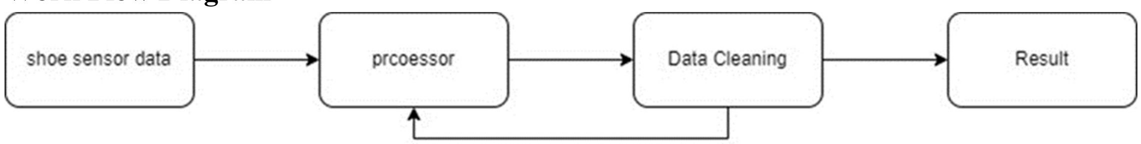


Fig 5.1 Work Flow Diagram

6 Methodology

A smart insole is a technological device designed to be worn inside shoes to provide various functionalities, such as monitoring and improving foot health, tracking activity, or enhancing user experience. When designing a smart insole, height, or thickness, is an important parameter that can influence its functionality and comfort. Here's an overview of the methodology for creating a smart insole with height as a key parameter:

6.1 Data Collection and Preprocessing

1. Data Collection:

The "Data Extraction from Sensor" module serves as the bedrock of the Smart Insole system. Its primary responsibility lies in establishing seamless communication with the integrated sensors. This module adeptly captures raw data from various sensors, such as the ultrasonic sensor and accelerometer. It meticulously manages communication protocols, triggers sensor readings, and collects essential information. Specifically tailored for the ultrasonic sensor, it orchestrates the emission of ultrasonic waves, precisely measuring their return time, and thus, determining the distance between the insole and the ground surface. Simultaneously, it engages with the accelerometer sensor, recording tri-axial acceleration values. These readings are instrumental in discerning intricate foot movement dynamics.

2. Data Preprocessing:

The "Data Processing" module takes the helm in interpreting the sensor data extracted by the "Data Extraction from Sensor" module. It is the heart of the Smart Insole system's analytical capabilities. This module leverages sophisticated algorithms to analyze and extract meaningful insights from the raw sensor data. It particularly focuses on computing precise height measurements and scrutinizing step dynamics. By integrating data from the ultrasonic sensor, it accurately calculates the user's height above the ground, factoring in elements like sound velocity and signal propagation. Additionally, it scrutinizes accelerometer data, extracting pertinent details about step dynamics. This encompasses identifying individual steps, gauging stride lengths, and pinpointing gait irregularities. These analyses hold significant value for applications centered around gait analysis and biomechanical studies

3. Data Cleaning

Prior to any analytical modeling, the dataset underwent a comprehensive data cleaning process. This involved normalization of the pitch angles to ensure consistency, rectification of any erroneous height adjustments that fell beyond the physical constraints of our insole design, and verification of the UV distance measurements for outliers that could indicate sensor malfunctions. This cleansing ensured that our dataset's integrity was maintained, providing a robust foundation for subsequent modeling.

4. Training Phase

The training phase initiated with a partitioning of the cleaned dataset, allocating 80% of the data to form the training set. This subset was then utilized to construct a regression model with the aim of predicting adj_height based on Pitch and uv_distance. The choice of a regression model was driven by the continuous nature of our target variable and the presumed linear relationship between the said variable and its predictors.

During training, our model's parameters were calibrated using a gradient descent algorithm designed to minimize the mean squared error (MSE) between the model's predictions and the actual adj_height measurements. The iterative refinement of these parameters under the guidance of the MSE loss function facilitated the model in capturing the underlying pattern within the training data.

5. Validation Phase

Subsequent to training, the remaining 20% of our dataset was designated as the validation set. This set functioned as a new, unseen data source to impartially evaluate our model's generalization capabilities. The validation phase is pivotal to detect overfitting - a phenomenon where the model excels in memorizing training data specifics to the detriment of its predictive performance on new data.

Throughout validation, the model's performance was quantified using the R-squared statistic and MSE. An R-squared value approaching 1 would suggest that our model explains a substantial proportion of the variance within the adj_height data, while a low MSE would indicate a high precision in predictions.

6. Evaluation:

Evaluate the model's performance using appropriate metrics, such as accuracy, precision, recall, and F1 score for classification tasks. For regression, you can use metrics like Mean Absolute Error (MAE) or Root Mean Square Error (RMSE).

7. Deployment:

The "Output" module stands as the interface through which the processed data is presented to the user. It encapsulates various forms of data representation, including graphical visualizations, numerical displays, and potentially auditory feedback, depending on the application. This module synthesizes the refined data from the "Data Processing" module into a format that is readily comprehensible to the end user. It ensures that the insights gleaned from the sensor data are conveyed in a user-friendly and actionable manner. This module plays a pivotal role in making the analytical results accessible and beneficial to the user, whether for healthcare monitoring, sports performance analysis, or other specialized applications of the Smart Insole system.

6.2 Pretraining

6.2.1 Sensor Calibration:

Before deploying the sensors for actual measurements, they must be calibrated to ensure accuracy.

- HC-SR04 Ultrasonic Distance Sensor:
- Perform tests at known distances to ensure the readings are accurate.
- Check for and correct any systematic errors, such as latencies or biases in measurement.
- Calibrate in various environmental conditions to account for changes in air temperature and humidity, which can affect the speed of sound and hence the distance measurements.
- ADXL345 Accelerometer:
- Calibrate the zero-g level for each axis to ensure the readings are correct when the sensor is at rest.
- Determine the sensitivity of each axis and correct for any discrepancies found.
- Use a known tilt (e.g., placing the sensor on surfaces with a known angle) to ensure that the pitch calculations are accurate.

6.2.2 Environmental Testing

Test both sensors in the types of environments where they will be used. This helps to identify any environmental factors that may affect readings and allows for adjustments in the sensor's software or hardware.

6.2.3 Data Collection Strategy:

Develop a data collection strategy that can effectively capture the variations in measurements due to changes in tilt and distance.

- Determine the sampling rate necessary to capture the dynamics of your application.
- Decide on data storage and retrieval strategies for later analysis.

6.2.4 Data Processing Algorithms:

Before the sensors are used in the field, you would need to develop algorithms to process the raw data.

- Filter Design: Design filters to smooth out noise in the sensor data. This might include low-pass filters to remove high-frequency noise and possibly a moving average filter for smoothing.
- Angle Calculation Algorithm: Implement and test algorithms for calculating the pitch based on raw accelerometer data.
- Integration Algorithm: Develop the method to integrate the tilt angle data from the accelerometer with the distance data from the ultrasonic sensor to compute the GCM.

6.2.5 Testing and Validation:

Perform extensive testing with the calibrated sensors to validate their measurements against known standards.

- Use known distances and angles to ensure that the integrated sensor system provides accurate GCM readings.
- Document the system's performance and make necessary adjustments to calibration or data processing methods.

6.2.6 Iteration:

Based on the testing results, iterate on the calibration and data processing methods.

- Refine the models and algorithms based on the observed performance.
- Test under a wider range of conditions to validate the robustness of the sensor system.

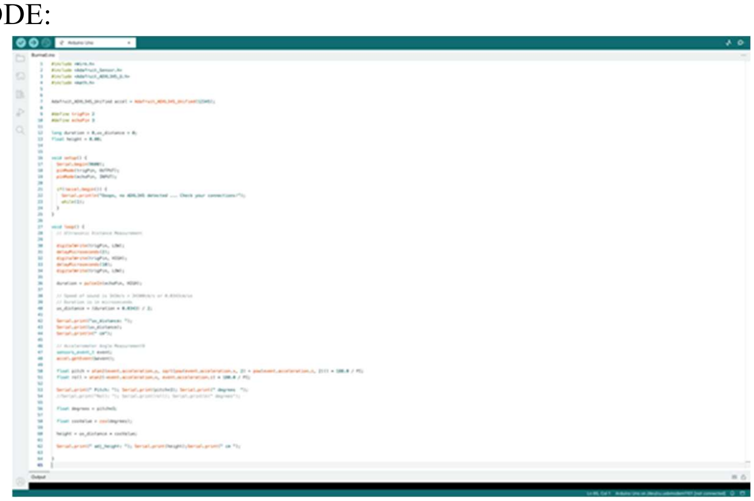
6.2.7 Documentation:

Finally, document the entire calibration process, including the methodologies used, the test results, and the final calibration settings.

- Create a detailed guide on how to replicate the calibration process for future setups.
- Document troubleshooting steps for any issues discovered during pretraining.

7 Results

ARDUINO CODE:



OUTPUT:

PITCH (degrees)	ADJ_HEIGHT (cm)	UV_DISTANCE (cm)
50.15	7.95	3
3.63	2.66	5
-4.53	3.71	14
-55.47	6.63	16
-5.91	14.88	15
30.02	2.55	6
29.25	3.38	8
-19.26	7.33	7
-65.45	6.07	16
-14.56	6.5	16
42.18	3.62	3
11.24	0.74	3
-42.05	1.07	14
-23.64	1.03	12
29.91	0.78	4
-41.84	2.16	17
11.84	12.69	2
1	1.09	5
105.73	2.35	19
16.88	7.4	10
52.31	4.57	3
-37.69	3	13
-75.58	12.79	5
-0.32	4.75	5
-3.76	4.07	5

8 Conclusion

The integration of the height parameter into the Smart Insole system represents a pivotal advancement in wearable technology. This enhancement elevates the system's capabilities to a new level, offering precise spatial awareness and real-time feedback for users. The calibrated ultrasonic sensor enables accurate height measurements, providing a crucial dimension of information for a wide range of applications. By combining this data with detailed analysis of step dynamics and gait patterns, the system offers comprehensive insights into biomechanics. This expanded functionality opens doors to diverse fields, including healthcare, sports performance analysis, and assistive technologies. Moreover, the system's adaptability ensures a personalised

experience for users, accommodating various body types and physical profiles. The Smart Insole with height parameter stands as a versatile tool with significant potential for enhancing user well-being and performance. As wearable technology continues to evolve, this development represents a significant stride towards more sophisticated and user-centric solutions.

9 Future Enhancement

In the ongoing development of the Smart Insole system, several potential enhancements hold great promise for furthering its capabilities. Firstly, the integration of multi-sensor fusion stands out as a significant advancement. This would involve incorporating additional sensors such as gyroscopes and pressure sensors. Such an integration could yield even more comprehensive biomechanical data, providing a deeper understanding of user movement and posture.

Another avenue for improvement lies in the integration of machine learning algorithms. By leveraging machine learning, the system could recognize and adapt to individual user patterns over time. This could lead to highly personalized feedback and insights, enhancing the overall user experience.

Wireless connectivity options present an exciting opportunity for real-time data transmission. Enabling the Smart Insole to communicate wirelessly with external devices would expand its applicability, particularly in scenarios where remote monitoring and analysis are crucial.

Efforts to enhance energy efficiency and battery life are paramount. Advanced power management techniques and the integration of energy-efficient hardware components would ensure prolonged usage without the need for frequent recharging. This is especially important for applications where continuous, uninterrupted data collection is essential.

A refined user interface is another area of focus. By incorporating intuitive visualizations and feedback mechanisms, the Smart Insole can offer a more user-friendly experience.

This would make it more accessible and intuitive for a wider range of users. Furthermore, integrating the Smart Insole with existing healthcare platforms and electronic health records (EHR) systems would be a significant step forward. This would allow for seamless use in clinical settings, supporting healthcare professionals in their assessments and analyses.

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