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Portable gait-asymmetry detection using low-cost hardware and machine learning

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Abstract: Gait analysis provides insights into human motion by examining how individuals walk. However, the high cost associated with gait centers prevents conducting gait analysis regularly, reducing opportunities for early detection and prevention of gait-related issues before pain or injuries occur. The approach presented in this paper integrates low-cost yet computationally powerful hardware with signal processing and machine learning to develop a wearable sensor node placed at the pelvis that continuously collects gait data, providing personalized gait analysis. By positioning the wearable at the pelvis, gait asymmetries can be captured accurately. The approach is validated in a laboratory experiment with 15 participants walking on a treadmill and verified in a free-moving environment. Results indicate that the wearable detects gait asymmetries effectively, enhancing applicability in both clinical and non-clinical settings, supporting rehabilitation and preventive care in a cost-efficient manner.

Keywords: Gait analysis, machine learning, wearable technology, Internet of Things.

1 Introduction

Human gait reflects complex coordination across the body, involving balance and mobility mechanisms that are susceptible to asymmetries caused by injury, aging, or by inherent body asymmetries [1]. Gait asymmetries can arise from injury compensation, muscle weakness, joint issues, or neurological conditions such as strokes and Parkinson's disease [2]. Physiological differences, such as leg length discrepancies or pelvic misalignment, as well as proprioceptive impairments and fatigue, also contribute to asymmetrical movement patterns. These asymmetries often reflect unique (for each individual) body adaptive strategies to maintain stability and minimize discomfort, highlighting the importance of personalized analysis [3]. Traditional gait analysis systems, though effective, are typically costly and confined to controlled environments [4]. With recent advances in machine learning (ML) and the reduction of sensor costs, new systems for portable gait analysis have been proposed [5]. Due to the rapid development of Internet of Things (IoT) and big data technologies, gait analysis based on ML methods have been proposed [6]. However, these innovations still have not found their way out of research and clinical environments to conduct gait analysis in everyday contexts, due to a lack of approaches that effectively obtain relevant personal gait information from the large amount of data being collected.

Thus, this study proposes collecting gait data exclusively from the pelvis, as the anatomical interface between the upper and lower body and efficiently analyze it using signal processing and ML models. By doing so, the system enhances portability while preserving critical insights into gait dynamics. This study focuses on gait-asymmetry detection through a dual approach: first, by extracting and comparing standard spatio-temporal parameters, and second, by examining dynamic movement patterns of the pelvis. By integrating these aspects, the system provides a deep understanding of functional body adaptations, offering enhanced accuracy in identifying gait asymmetries and their underlying causes. This approach highlights functional body adaptations, offering a deeper understanding of human gait beyond traditional methodologies that assume an "ideal" gait pattern. ML enhances the detection of gait events and asymmetries, improving accessibility for broader populations. Combining sensor placement on the pelvis with advanced analytics creates an efficient, low-cost system suitable for clinical and non-clinical applications alike.

The rest of the paper briefly introduces the methods to conduct portable gait analysis and describes the tests and results that validate the methods. Finally, the conclusions highlight future work in the field of portable gait analysis.

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2 Methods

2.1.1 Gait biomechanics

Human gait follows a periodic pattern known as the gait cycle, which consists of a full stride from the initial contact of one foot to its next ground contact [1]. This cycle is divided into two main phases, (1) the *stance* phase, where the foot remains in contact with the ground, and (2) the *swing* phase, where the foot moves forward. The stance phase includes subphases, such as heel strike, double-support time (when both feet are on the ground) and foot flat, which facilitate weight distribution and stability. Additionally, the double-support time during the stance phase enhances balance and is particularly relevant for individuals with mobility impairments.

The stance phase includes two key events: initial contact (IC), when the heel first touches the ground to absorb impact, and toe-off (TO), when the foot pushes off to propel the body forward. In this paper, gait analysis is conducted during different gait phases to detect asymmetries based on the acceleration data. The data is collected by a portable sensor node (wearable), consisting of a microcontroller and an inertial measurement unit (IMU). The method used to conduct gait analysis based on the acceleration data is divided into to steps:

1. *Gait-phase detection algorithm*: The algorithm is based on long-short-term-memory (LSTM) networks, used to segment gait phases, including double-support times and heel strikes of each leg. The LSTM network is trained to automatically detect the two gait phases double support and heel strike, setting the basis for automating the segmentation of the complete gait cycle.
2. *Asymmetry detection*: Two methods are used to detect gait asymmetries in the abovementioned gait phases:
   - *Spatio-temporal analysis*, which is a common analysis to detect anomalies in individual gait when compared to “golden standards”. In this paper, the goal is to identify significant discrepancies in the double-support time phase to reveal gait adaptations in individuals with injuries.
   - *Amplitude and signal-shape analysis*. The dynamic movement patterns of the pelvis are analyzed, going beyond deviations from the golden standards. Signal amplitudes from the acceleration data are used to detect asymmetrical impacts during heel strikes. Gait asymmetries that derive into asymmetrical musculoskeletal development, which is an unconscious human adaption, can be identified to predict and thus avoid pain or injuries in the long term.

2.1.2 A portable gait analysis system

The portable gait analysis system is a wearable that includes an Arduino MKR Wi-Fi 1010 and a Bosch BNO085 IMU, providing a compact, low-cost solution. The strategic placement of the IMU on the sacral region of the pelvis minimizes soft tissue artifact interference because it collects gait data from a low-fat part of the body. The placement captures the role of the pelvis as a central biomechanical link between the upper and lower body, facilitating standardized and reliable data collection. Issues in the upper body manifest in altered pelvic motion, while irregularities in the lower body are directly translated into the dynamics of the pelvis, offering comprehensive insights into gait patterns.

Placing a single sensor on the pelvis offers multiple advantages. First, it significantly reduces the overall cost of the system, making it more accessible for widespread use. This low-cost approach facilitates large-scale data collection and minimizes errors during measurement. Additionally, using a single sensor standardizes data collection, avoiding interpretability issues caused by soft tissue artifacts and body type variations that can arise with multiple sensors placed on different parts of the body.

By measuring gait asymmetries at the pelvis, not only can spatio-temporal parameters be extracted, but the dynamics of pelvic movement during gait can also be analyzed. The wearable that is placed at the pelvis with the help of a belt is depicted in Figure 1, including all its hardware components.

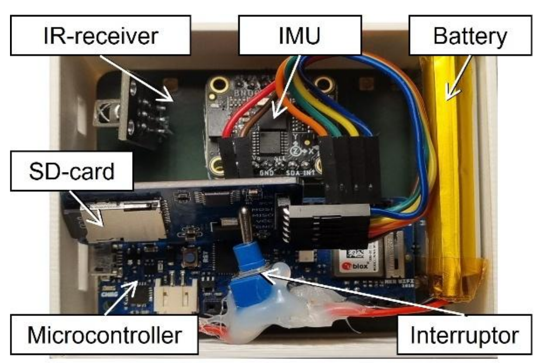

Figure 1: Hardware components of the wearable forming the portable gait analysis system.

3 Validation and results

In this section, the setup of the validation test is briefly outlined, followed by the results of conducting gait analyses on 15 participants. The goal of the test is to prove that the portable gait analysis system can detect gait asymmetries based on the methods explained in Section 2.

3.1.1 Validation test setup

The participants completed a questionnaire on health and fitness before the experiment. Then, they carried the wearable using a securely fastened belt and stood upright for calibration to ensure accurate data collection. To validate the accuracy of the IMU measurements, the system was tested using a treadmill with load cells to detect the double-support times. The load cells measure ground reaction forces during walking. The load-cell measurements served as a reliable external reference for identifying IC and TO events, key indicators of the double-support phase. The experiment was designed to include walking at four different speeds, with each speed session lasting 50 seconds, equivalent to capturing 5000 data samples. The data samples were stored on the SD card of the wearable and then transmitted to a laptop for conducting gait analysis in Matlab.

3.1.2 Training and validation of the LSTM network

To identify gait phases and investigate asymmetries, an LSTM network was trained and tested. The initial step involved performing manual labeling for IC and TO. This procedure is labor-intensive and demands significant concentration. To guarantee the accuracy of the labels, a verification algorithm was implemented to confirm the correctness of the labelled data, ensuring that the LSTM network is not trained on erroneous information. To train the LSTM, 70% of the dataset was allocated for training, while the remaining 30% was reserved for testing.

The confusion matrix in Figure 2 shows the LSTM performance for gait-event detection on the test dataset, comparing true class labels with predicted. For the double-support left stance phase (in which the left leg is in contact with the ground first), the true positive rate was 96.2%, with

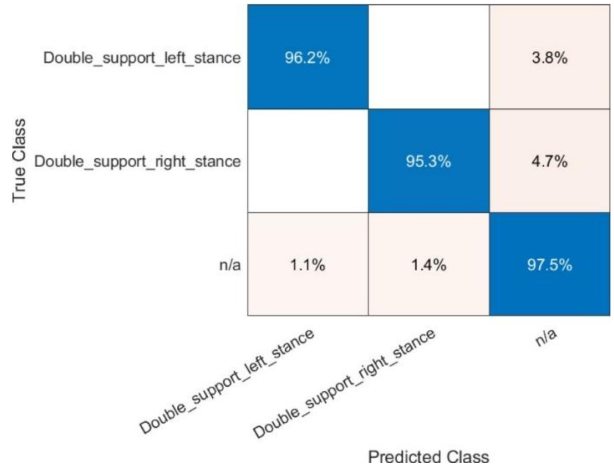

Figure 2: Confusion matrix representing the result of the automated data labeling conducted by the LSTM network.

3.8% misclassified as “n/a”. For double-support right stance, the true positive rate was 95.3%, with 4.7% misclassified as “n/a”. The “n/a” class was correctly classified 97.5% of the time, with false positives of 1.1% for double-support left stance and 1.4% for double-support right stance.

3.1.3 Spatio-temporal gait analysis

After the double-support times are accurately determined by the LSTM network, the stance time and swing times were derived. With these parameters, stride duration and cadence were easily calculated. It was observed that individuals with injuries showed a distinct difference in double-support times. An exemplary result is presented in Table 1, where the double-support time, measured in centiseconds (cs), for the right leg is longer than for the left leg. The test subject has a partial tear of one of the cruciate ligaments in the right knee. The prolonged double-support time indicates that the subject relies more on both legs being in contact with the ground, which helps to distribute weight and reduce stress on the injured knee. In healthy individuals, the double-support time measurements were much more consistent, with the average difference not exceeding 0.4 cs, indicating a stable and uniform gait pattern. While useful, spatio-temporal metrics may miss subtle gait discrepancies indicating underlying issues. To achieve a more comprehensive analysis, a shape analysis on the IMU data was conducted, as shown in the following subsection.

Table 1: Asymmetries observed in the double-support times.

Parameters	L&R stance	L stance	R stance
Double-support time	13.75±1.19	13.69±1.24	13.85±1.18
Stance time	56.04±2.28	56.55±2.20	55.50±2.37
Swing time	42.29±1.95	41.64±2.34	42.86±1.33
Stride time		111.08±2.36	
Cadence time		110.23	

3.1.4 Analysis of gait dynamics

The results of one participant are shown in this subsection to exemplify the limitations of studying gait analysis using spatio-temporal metrics and comparing them using golden standards. During the tests, a participant reported left-thigh discomfort, yet spatio-temporal metrics such as cadence and double-support times showed no asymmetries between legs.
This suggested a normal gait under basic observation. However, after recognizing the inability of spatio-temporal metrics to detect a known injury, a more detailed analysis using the collected acceleration data was conducted. In Figure 3, a noticeable difference in amplitudes between the labelled points 5 and 6 suggest that the body decelerates the movement before IC with the left foot to reduce impact, resulting in deceleration of the anterior-posterior movement. Additionally, the heel strike impact shows a lower amplitude, likely due to the deceleration mentioned above.

To test this hypothesis, the roll and yaw velocities was analyzed. The left stance showed significantly smaller maximum amplitudes just before IC, indicating slower movement, while the yaw velocity was higher in the right stance, suggesting increased rotational speed in the transverse plane. Figure 3 further highlights differences in the sagittal plane, where the right stance follows the expected pattern, but the left stance fails to reach the same amplitude.

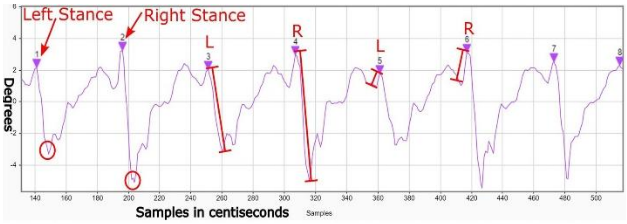

Figure 3: Acceleration data in the z-axis of a subject with discomfort in the left thigh.

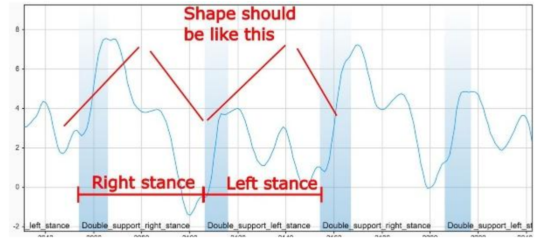

Figure 4: Asymmetry in pelvis rotation due to Injury.

During the tests, other asymmetries linked to gait dynamics were obtained. The asymmetry depicted in Figure 4 is linked to a rotated pelvis, likely a result of a past cruciate ligament injury, which was reported by a participant. Figure 4 shows the results of acceleration forces during double-support times of the participant, which 0was experiencing chronic pain. The participant was informed of the result of the test. Results of the gait dynamic analysis may thus give information of underlying injuries causing pain.

4 Summary and conclusions

Combining wearable technology and ML, the portable gait system presented in this paper detects asymmetries with high precision and efficiency. A gait-phase detection algorithm using LSTM networks, identifies gait asymmetries in spatio-temporal metrics, and signal amplitude analysis, examining pelvis dynamics to uncover unconscious gait adaptations. The approach enables early detection of asymmetrical muscular development, helping to prevent long-term pain or injuries. Future work will focus on feedback mechanisms and incorporating data from subjects with other gait abnormalities.

Author Statement

The author state no funding involved. Authors state no conflict of interest. Informed consent has been obtained from all individuals included in this study.

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