

COMPARATIVE ANALYSIS OF UWB AND IMU FOR CONSTRUCTION SAFETY MONITORING

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Abstract

This study compares Ultra-Wideband (UWB) location-based tracking against Inertial Measurement Unit (IMU) gait-based activity recognition for construction safety monitoring. Experiments were conducted in a controlled environment simulating construction hazards (walking on planks, scaffolding, and mezzanines). Results indicate a trade-off: IMU classifiers effectively detect kinematic changes (81.6% accuracy) but fail in spatial awareness, whereas UWB successfully identifies elevation zones (92.3% accuracy) but suffers from vertical signal noise. Rather than viewing these limitations as failures, this study establishes the operational boundaries of standalone UWB and IMU systems in vertical environments, providing empirical baseline parameters for future sensor fusion design.

Introduction

The construction industry is known for its hazardous work environment (Soltanmohammadlou et al., 2019). In 2023, the European Union reported the highest incidence of non-fatal accidents at work within the construction sector, recording 2,899 accidents per 100,000 employed persons (Eurostat, 2025). These statistics highlight the need for targeted interventions to improve the health and safety standards of the construction sites. One important aspect is tracking the site personnel which can help to inhibit occurrence of the accidents by taking the right measures, also enabling the rapid emergency response if an accident occurs. Traditional safety monitoring relies on direct human observations and could not provide real-time coverage of large and complex construction sites (Akhavian & Behzadan, 2016; Zhang et al., 2018). However modern technologies allow real-time tracking of workers, material and equipment. Among these, Ultra-Wideband (UWB) for localization and Inertial Measurement Units (IMU) for activity recognition have emerged as prominent solutions, offering different approaches to safety monitoring.

The UWB positioning system is widely considered as standard for real-time tracking in construction, ensuring centimeter-level error with a clear line of sight (LOS) (Naheem & Kim, 2022). Unlike other wireless technologies such as BLE and Wi-Fi, which rely on Received Signal Strength Indicator (RSSI), UWB operates based on time-of-flight (ToF) measurements. Its

short wavelength and high bandwidth contribute to robustness against multipath fading and interference when compared to alternative wireless technologies (Rao et al., 2022). In construction environments, UWB enables reliable real-time positioning of workers, materials, and equipment, particularly in open and unobstructed settings.

Despite its advantages over other wireless technologies, UWB faces limitations under Non-Line-of-Sight (NLOS) conditions, as its positioning accuracy degrades when signals are obstructed by reinforced concrete elements and steel reinforcements commonly found on construction sites (Li & Li, 2025). NLOS leads to disappearances of worker's positions. Another drawback of UWB is the requirement of system setup. The UWB system comes with an upfront cost and needs time and effort to set the anchor sensor throughout the construction site with precise georeferencing before tracking can begin.

An IMU is a micro-electromechanical system (MEMS) sensor package that consists of a 3-axis Accelerometer, 3-axis Gyroscope and generally a magnetometer to measure linear acceleration, angular velocity and magnetic field strength, respectively. By integrating these measurements, position relative to a starting position can be determined (Rao et al., 2022; Leitch et al., 2023). IMU data offers a complementary perspective by capturing both the type of activity and its spatial context (Trigo et al., 2025). Unlike location-based systems, IMUs are not affected by NLOS conditions, enabling uninterrupted tracking (Li & Li, 2025), and their integration into smartphones further improves accessibility. Nevertheless, IMU-based approaches are limited to relative tracking rather than absolute positioning.

In safety-critical construction applications where absolute positioning is required, UWB enables proactive safety measures such as virtual fencing and collision avoidance (Teizer et al., 2008). However, environmental clutter significantly degrades accuracy; metallic obstructions can increase positioning errors from 0.4 m to 1.2 m due to multipath effects (Shahi et al., 2012). Geometric constraints also play a role, as linear anchor layouts cause Dilution of Precision (Maalek & Sadeghpour, 2013). Kılıç et al. (2025) demonstrated that for the MDEK1001 sensors, body placement is decisive: head-mounted tags achieve >99% signal reception by maintaining Line-of-Sight.

In contrast, IMU-based approaches are primarily employed to identify and classify worker activities rather than to provide absolute positioning. Akhavian & Behzadan (2016) and Zhang et al. (2018) demonstrated that sensors embedded in smartphones can reliably recognize construction tasks. However, IMUs do not offer a fixed spatial reference; Li & Li (2025) explain this limitation through accumulated errors, where sensor noise and environmental vibrations progressively distort the estimated trajectory, causing rapid drift and limiting the suitability of standalone IMUs for independent georeferencing.

Consequently, this study presents a comparative analysis of two commonly used approaches: i) infrastructure-dependent UWB systems, which require prior installation, and ii) IMU-based tracking available on standard smartphones. While both sensing modalities have been explored in general tracking applications, this work focuses on experimentally evaluating their performance across different walking modes in complex, multi-level construction environments (e.g., scaffolds, planks, and mezzanine levels). Rather than aiming to identify a single comprehensive solution for continuous safety monitoring, the goal is to examine the practical trade-offs between location-based positioning (UWB) and motion-based recognition (IMU), and to highlight the conditions under which each approach performs more reliably.

Methodology

To evaluate the different methods of classification of walking activity, a multi-sensor data collection was held in a controlled structural engineering laboratory environment. This experiment involved 5 male participants, composed of graduate students and structures lab technicians with ages ranging 25 to 60 years.

IMU of Apple iPhone devices was utilized. 3-axis accelerometer and 3-axis gyroscope of the IMU captured linear acceleration and angular velocity data with App Store achievable smartphone application. The IMU data was captured at a sampling rate of 100 Hz. Two smartphones were placed on the participants' bodies. One of the smartphones was placed on the lumbar region of the participants to capture data close to the body center of mass. The other smartphone was placed in the right front pocket of the participant, representing the practical sensor placement (Figure 1).



Figure 1: Participant instrumented with a UWB tag (hardhat) and smartphones (pocket and lumbar) for data collection.

Location tracking within the controlled experiment setup was performed using 11 Qorvo MDEK1001 Ultra-Wideband (UWB) Transceiver Development Kit modules manufactured by Qorvo. Nine of the UWB sensors were assigned as anchor nodes and were positioned within the experiment area to ensure full coverage possible. The distances between the anchor nodes were measured with a total station and the relative coordinates of the nodes were entered into the Qorvo application available in the App Store. One of the UWB sensor was assigned as a tag and was mounted on the front of the hardhat worn by the participants (Figure 1). Another UWB sensor was assigned as a listener and connected to a Raspberry Pi 5 microcomputer. The listener sensor communicated with the tag sensor and received the relative position among the experiment setup. The location data was collected during each participant's experiment and saved in the CSV format at the end of each trial.

Each participant followed the same predefined circuit four times for their turn. The circuit included four walking scenarios: normal walking, elevated walking, plank walking and scaffolding walking. Normal walking refers to participant's walking on the ground level. Elevated walking refers to participant's walking on the mezzanine level. Plank walking refers to participant's walking on a plank. The plank has 3 m length, 15 cm width and 20 cm height above the ground. Scaffolding walking refers to walking on a scaffold structure.

The ground truth was established by capturing video recordings of all the trials. The video recordings were captured in 720p at 60 fps. Video recordings were later used for labeling the IMU and UWB data.

The raw data collected from the multi-sensor systems were processed and synchronized to enable a direct comparison between the IMU-based system and the UWB-based system. All processing steps were implemented using Python.

The video recordings were labeled using ELAN - Linguistic Annotator software to establish the ground truth (Figure 2). Precise start and end timestamps were generated for five different walking activities on different surfaces: normal walking on ground level(n_walk), walking on a plank(p_walk), walking on mezzanine level(e_walk), walking on upper level of the scaffolding

(s_walk_upper), and walking on lower level of the scaffolding (s_walk_lower). The raw IMU and UWB data were synchronized with these labels using Unix timestamps, and non-relevant segments were removed from the dataset.

A 4th-order Butterworth low-pass filter with a cutoff frequency of 30 Hz was applied to both accelerometer and gyroscope signals to minimize the impact of environmental noises. The IMU data were segmented into sliding windows of 2.0 seconds with 50% overlap. For each window, statistical and frequency-domain features were extracted from the three orthogonal axes of the accelerometer and gyroscope, as well as their calculated magnitudes. A total of 13 features were computed per channel, including mean, standard deviation,

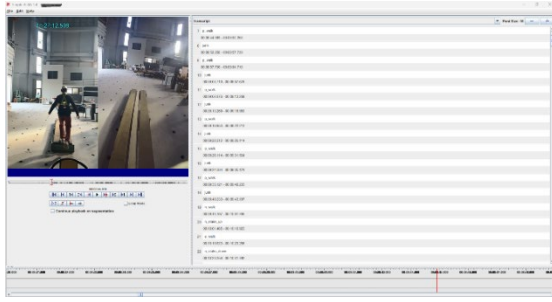


Figure 2: Ground truth labeling interface using ELAN software to segment walking activities

root mean square (RMS), skewness, kurtosis, interquartile range, Shannon entropy, dominant frequency, and spectral entropy.

In terms of determining the optimal configuration for activity recognition, a systematic grid search analysis was conducted. We evaluated sliding window durations ranging from 0.5 to 3.0 seconds, overlap ratios between 25% and 75%, and various feature subsets. Additionally, multiple machine learning algorithms such as linear models (Logistic Regression, LDA), probabilistic models (Naive Bayes), distance-based methods (k-NN), and tree-based ensembles (Random Forest, XGBoost) were compared. The Random Forest classifier ($N = 100$ trees), paired with a 2.0-second window and 50% overlap, consistently yielded the highest F1-score and generalization performance. Consequently, this configuration was selected for the final analysis. Performance was evaluated using a Leave-One-Subject-Out (LOSO) cross-validation scheme.

The UWB data was processed using a rule-based spatial algorithm that relies on the participant's position relative to the zones defined in the experimental setup. To mitigate signal jitter and non-line-of-sight (NLOS) outliers caused by environmental factors, a context-aware smoothing pipeline was implemented. Rather than applying a blanket filter, the raw coordinate data was first segmented based on hardware disconnections (time gaps > 1.5 seconds) and trial state changes. A rolling median filter (window size = 5) was then applied independently to each segment. This approach prevented the blurring of spatial boundaries

between distinct activities while effectively removing anomalous positional spikes.

The UWB tags were mounted on the participants' hardhats. To estimate the vertical position relative to the walking surface Z_{foot} , the participant's standing height ($H_{participant}$) was subtracted from the sensor's Z-coordinate (Z_{tag}), as formulated in Equation (1):

$$Z_{foot} \approx Z_{tag} - H_{participant} \quad (1)$$

The core classification logic involved checking whether the coordinates (X, Y, Z_foot) fell within predefined 3D bounding boxes representing the walking zones. A significant challenge was the inherent noise in the UWB vertical measurements. Statistical analysis indicated a standard deviation of approximately $\sigma \approx 0.6$ m in the Z-axis for ground-level activities. To address this issue in a systematic manner and avoid arbitrary parameter selection, an empirical sensitivity analysis was conducted to determine appropriate spatial tolerances (buffers). As illustrated in Figure 3, multiple scenarios were evaluated by testing three horizontal (X-Y) to vertical (Z) expansion ratios (1:2, 1:3, and 1:4), systematically increasing the horizontal tolerance in 0.05 m increments. For each configuration, Macro F1-score and overall accuracy were computed to identify the most suitable noise mitigation threshold. The 1:3 expansion ratio demonstrated the most robust performance, establishing a clear "elbow point" at the 0.4 m horizontal mark where the Macro F1-Score plateaued. This suggests a reasonable balance between noise reduction and spatial precision, leading to the selection of final tolerances of 0.4 m horizontally and 1.2 m vertically.

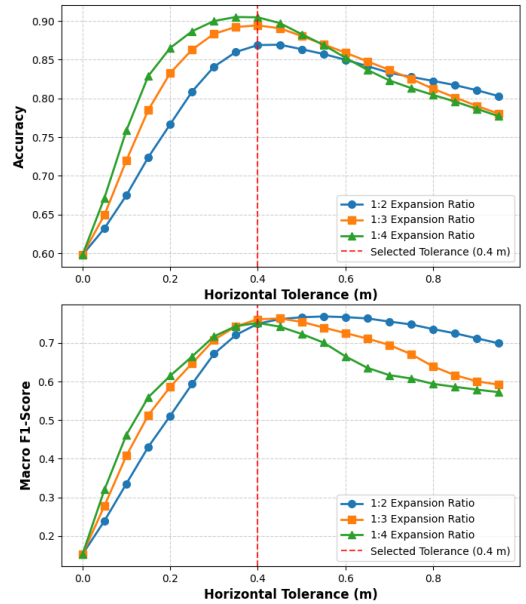


Figure 3: Empirical sensitivity analysis illustrating the effect of horizontal tolerance increments on Accuracy (top) and Macro F1-Score (bottom) across three spatial expansion ratios.

It is noted that these tolerance values are specific to the sensor noise characteristics and the spatial layout of this specific construction site. The point-based spatial predictions were aggregated to match the IMU processing window. The UWB data were segmented into 2.0-second

windows with a 50% overlap, and the final label for each window was determined via majority voting of the rule-based predictions within that window.

Results

In this section, the classification performance of the proposed systems is presented. First, we analyze the impact of sensor placement (Lumbar vs. Pocket) on activity recognition. Second, we compare the best-performing inertial configuration against the UWB rule-based system.

Table 1: Performance comparison of IMU sensor placement (Lumbar vs. Pocket) ($N = 4$)

Placement	Accuracy	Precision	Recall	F1-Score
Lumbar	79.57%	0.327	0.358	0.340
Pocket	75.20%	0.301	0.331	0.314

Table 2: Comparative performance of the Lumbar IMU and UWB systems ($N = 5$)

System	Accuracy	Precision	Recall	F1-Score
IMU	81.56%	0.443	0.376	0.372
UWB	92.28%	0.713	0.808	0.732

In terms of determining the optimal IMU placement, we compared the lumbar region and right front pocket positions. Due to data loss for one participant in the pocket dataset, this specific comparison was restricted to a subset of participants ($N = 4$) to ensure a valid direct comparison. Table 1 summarizes the performance metrics. The Lumbar placement consistently outperformed the Pocket placement across all metrics.

We next compared the better-performing IMU configuration (Lumbar) against the UWB rule-based spatial classifier. Since complete lumbar IMU data were available for all participants, this comparison was conducted using the full dataset ($N = 5$). The results, presented in Table 2, demonstrate a significant performance divergence between the two approaches.

Although the IMU system has a relatively high overall accuracy (81.56%), its F1-score has a low value (0.372). The confusion matrices (Figure 4) provide insight into this discrepancy. The IMU-based system failed to capture spatial context; samples belonging to Elevated Walk (e_walk) and Scaffolding Walk (s_walk) were predominantly misclassified as Normal Walk (n_walk).

On the other hand, the UWB-based system achieved a dramatically higher F1-score of 0.732. It correctly identified 99% of the (e_walk) samples. The UWB-based system successfully distinguishes the mezzanine level from the ground floor.

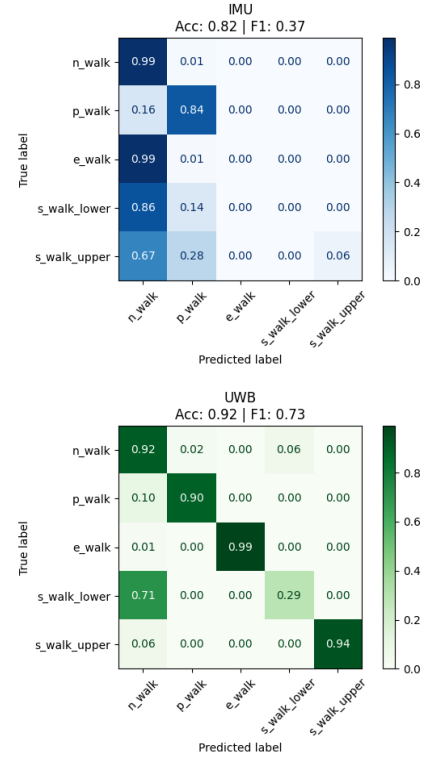


Figure 4: Confusion matrices for IMU(top) and UWB(bottom).

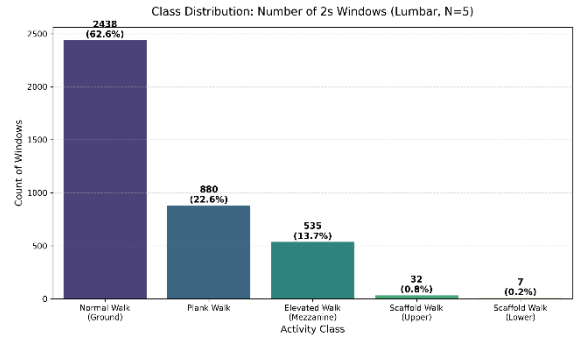


Figure 5: Class Distribution

Discussion

The primary objective of this study was to evaluate and compare UWB and IMU technologies for enhancing construction safety, specifically in monitoring worker activities across varying elevation levels. By analyzing sensor performance in controlled experiment conditions, this research sought to identify the operational limitations and complementary strengths of each system. Within this context, the results highlight significant trade-offs between the two systems.

One of the most essential outcomes of this study is the sensor placement's impact on the result. The lumbar placement outperformed the pocket placement which is consistent with the literature. Teng et al. (2024) highlighted the pelvis region as the single optimal sensor location due to its proximity to the body's center of mass. In their analysis of 12 body locations, the pelvis region consistently outperformed the upper thigh.

The observed discrepancy exists in the IMU results between high Accuracy (81.6%) and low F1-Score (0.37) can be attributed to class imbalance. As Figure 5 shows, Normal Walking (*n_walk*) constitutes the vast majority of the data windows. Consequently, the IMU classifier frequently predicts Normal Walking, inflating accuracy while failing to detect minority classes, as reflected by the low F1-score. This output aligns with the findings by Zimbelman & Keefe (2021) who observed that forestry workers spent 93% of their time in a 'Clear' (idle) state, which similarly degraded the model's ability to detect rare activities.

The UWB system successfully resolved the height awareness opposed to the IMU, achieving a Recall of 0.808. However, it reveals a specific weakness in differentiating between scaffold levels. While the system perfectly separated the Mezzanine (*e_walk*) from the Ground (*n_walk*), it struggled to separate the Lower Scaffold (*s_walk_lower*) from the Upper Scaffold (*s_walk_upper*). This limitation is directly attached to the spatial rule used to mitigate sensor noise. In this experimental setup, the optimal vertical tolerance exceeded the height difference between scaffold levels, resulting in class overlap.

The most critical finding is the IMU's inability to distinguish between ground level normal walking and elevated walking. Despite achieving 81.56% accuracy, the IMU system exhibited nearly zero recall for elevated walking classes due to the absence of absolute spatial awareness. This is expected, as the kinematic gait patterns of walking on a concrete ground floor and a concrete mezzanine are largely indistinguishable from an inertial sensing perspective. This limitation aligns with findings by Naheem and Kim (2022), who emphasized that while IMUs are effective for relative step detection, they require an external reference like UWB to resolve global positioning and correct for drift.

The analysis demonstrates the distinct operational boundaries of each system. IMU excels at detecting activity dynamics such as distinguishing the balance corrections in (*p_walk*) vs. (*n_walk*) but is blind to location. UWB excels at detecting general zones (Ground vs. Mezzanine) but is limited by the trade-off between noise mitigation and spatial resolution.

Practical Implementations and Real-World Limitations

While the controlled laboratory environment provided a necessary baseline for isolating sensor capabilities, deploying these technologies on active construction sites introduces practical complexities.

The current study utilized a localized network of nine UWB anchor nodes to ensure full coverage of a single laboratory space. Scaling this infrastructure to a continuously evolving, multi-story construction site presents significant logistical challenges. Maintaining precise georeferencing for dozens of UWB anchors across an active site requires constant recalibration and high upfront costs. In contrast, the IMU approach is highly

scalable, as it leverages standard smartphones already carried by site personnel, requiring zero additional infrastructure.

The UWB system achieved a high spatial accuracy (92.3%) in a controlled setting. However, real-world construction sites are characterized by dynamic clutter such as moving heavy machinery, dense worker interactions, and temporary material stockpiles. The dynamic clutter induces Non-Line-of-Sight (NLOS) conditions. Furthermore, as previously established in literature (Shahi et al., 2012), a critical operational challenge for UWB is multipath interference caused by metallic obstructions. Reinforced concrete and steel scaffolding are common in vertical construction hence these dynamic obstructions and reflections are expected to degrade the baseline accuracy established in this study.

To address these real-world interferences, future deployments should monitor UWB data quality in real-time. When the positioning signal is stable and physically consistent, UWB spatial tracking remains the primary source. However, when the signal exhibits physically implausible movements, the system should dynamically shift reliance to IMU channel.

Conclusion

This study presented a comparative analysis of UWB-based localization and smartphone IMU-based gait analysis in terms of construction safety monitoring. The experimental outputs highlight a distinct trade-off between activity recognition and spatial context. While the IMU-based system effectively detected kinematic changes such as balance differences on narrow planks, its sensitivity to location was worse. The IMU-based analysis failed to distinguish between normal ground-level walking and elevated walking. Conversely, the UWB system provided critical spatial awareness, successfully identifying elevated zones like mezzanines. However, it performed worse in identifying walking on scaffolding due to noise buffering limits.

Rather than framing these limitations as shortcomings of the technologies, this study aims to better understand their practical operating conditions in complex, multi-level construction environments. The findings highlight key limitations, such as the spatial ambiguities associated with IMU-based tracking and the vertical noise observed in UWB measurements. By documenting these behaviors, the study provides a useful empirical reference for future work. Building on these insights, future research can explore more practical sensor fusion approaches that combine the complementary strengths of IMU-based activity recognition and UWB-based positioning, with the goal of improving reliability in real-world construction settings.

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