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PROXIMITY DETECTION TECHNIQUES FOR UBIQUITOUS COLLABORATION

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ABSTRACT
Proximity detection works in conjunction with other enabling technologies and becomes an essential requirement for interaction in a ubiquitous collaborative environment. Mobile and embedded systems are increasingly widespread with advancements in technology; hence, detecting and tracking the location of users or objects in that environment becomes crucial for context-sensitive communication, system behavior, and service delivery. This paper aims to review techniques for proximity detection, exploring their applications in ubiquitous collaboration. We explore fundamental enabling technologies, including RFID, Bluetooth, Wi-Fi, ultrasonic, and infrared systems, thoroughly focusing on their principles of operation, benefits, and limitations. From collaborative workspaces and location-based services to innovative environments, the paper presents a range of real-world applications and acknowledges implementation challenges, including privacy, security, interoperability, and scalability. Several case studies are presented for successful deployments, best practices, and ongoing research trends. With this evaluation, we provided insights and recommendations to aid further research and system design in proximity-aware ubiquitous collaboration systems.
Keywords: Proximity detection, ubiquitous computing, collaborative systems, context awareness, RFID, Bluetooth, intelligent environments.

I. INTRODUCTION

In the context of ubiquitous computing, where innovative environments anticipate user interaction, proximity detection has emerged as a key feature to enable user-device interaction. Modern systems enable collaboration across silos in various domains, including education, healthcare, industry, and enterprise [1]. Proximity awareness enables the understanding of real-time context and spatial relationships, which is crucial for effective collaboration across disciplines. Enhancing systems responsiveness and interactivity improves user experience, allowing for a more natural interface.
Between 2021 and 2025, the proliferation of advanced sensing and wireless communication technologies greatly enhanced the potential for accuracy in proximity detection. There are now various approaches for detecting presence, movement, and orientation, including Bluetooth Low Energy (BLE), Radio Frequency Identification (RFID), Wi-Fi-based sensing, ultrasonic, and infrared sensors [3]. While each technology offers a unique approach, they differ in range, accuracy, energy consumption, and integration complexity. Automation of context-aware systems that enable service mobilization removes the need for direct human mediation. These technologies enable context-aware service triggering and device-user coordination [12].
In smart collaborative environments, proximity detection is helping optimize user interactions in various novel ways. Smart workspaces recognize and personalize digital interfaces for participants; educational systems perform roll call to start group activities based on student location; and healthcare devices monitor caregivers' proximity and adjust task

allocation accordingly [30]. These scenarios demonstrate the potential of proximity-based technologies to enhance human-system interactions, fostering more flexible, responsive, and context-aware relationships [15].
The implementation of such systems presents several technical and ethical challenges. Privacy is always a major concern, especially when users may be monitored without their knowledge or data collected without explicit consent [5]. Vendor dependence for device integration often imposes limitations on scalability, while high sensor density within a given area can result in signal noise, which can impair detection accuracy [34]. Designing effective systems that ensure user trust, reliable operation, low energy consumption, and minimal enforcement of restrictive policies is very challenging [14,32].
These trends and challenges should be considered in support of advancing collaboration, which can be experienced everywhere [16]. The combination of new expectations set by users and the evolution of smart infrastructure makes the case for reliable, scalable, secure, and interoperable proximity detection systems [9]. With continued efforts in research and development for this area, adaptive, user-centric, and efficient collaborative environments will inevitably place focus on enabling technologies based on proximity detection [17].

II. RELATED WORK

The recent developments in wireless communication protocols and sensor technologies that improve proximity detection within ubiquitous collaborative systems is a significant leap towards modernization [28]. The sensing methods used in BLE and Wi-Fi have been studied highly, owing to their good balance of power consumption, signal strength, and ease of integration with portable and IoT devices [2]. The methods of BLE beaconing and Wi-Fi fingerprinting enable precise indoor localization by analyzing changes in RSSI, CSI, and signal timing, which facilitates near real-time context inference crucial for synchronous collaborative interactions in closed spaces [11].
RFID technology, particularly in the passive and semi-passive configurations, has been utilized for object identification and proximity-based triggering within intelligent environments [10]. Recent hybrid architectures that combine RFID with BLE (Bluetooth Low Energy) or UWB (Ultra-Wideband) aim to mitigate problems such as multipath fading, tag collision, and limit the read range [8,31]. The systems utilize modulation of signals and Time of Flight (ToF) measurements to enhance spatial resolution and minimize interference, thereby improving the reliability of proximity sensing in dense deployments, such as collaborative manufacturing floors and interactive exhibits [18].
In the realm of precise short-range distance measurement, ultrasonic and infrared (IR) proximity sensors remain of utmost importance [19]. The operation of ultrasonic sensors is based on the propagation of ultrasonic waves and the precise measurement of the time it takes for the echoes to return [20]. This ability enables the detection of motion and presence by calculating the distance with an accuracy of a few centimeters [26]. Additionally, IR sensors provide directional distance information even with slight electromagnetic disruptions, making them ideal for augmentation with IMUs and ambient light sensors to increase contextual awareness and user intent understanding in collaborative tools and augmented reality systems [21].
The use of continuous proximity sensing techniques introduces a risk to user privacy, but at the same time, it creates an incentive for privacy-preserving solutions that seek to balance user privacy and data utility [24]. Proposals to mitigate the risks posed by data exposure include techniques such as data anonymization, homomorphic encryption, and edge computing, which are performed on the perimeter of the network [4]. In addition, blockchains enable the creation of tamper-proof distributed ledgers, improving data security and access control in IoT ecosystems, which also address the weaknesses faced with centralized collection and processing of proximity data [7,27]. These techniques strengthen susceptibilities of intrusive proximity data aggregation and processing [6,13].
The application of machine learning techniques and sensor fusion approaches have improved the flexibility and precision of proximity detection systems [29]. Users are recognized, and complex spatial-temporal patterns within dynamic collaborative environments are inferred through the analysis of multimodal sensor data streams using advanced deep learning techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) [22,33]. These systems utilize adaptive thresholding mechanisms, outlier detection, and feedback-based calibration to maintain operational efficiency under diverse environmental conditions, user densities, and device diversity, thereby expanding the limits of elite standards in scalable and ubiquitous collaboration frameworks [25,23].

III. PROPOSED METHOD

The demand for immediate interaction within ubiquitous collaboration systems necessitates strategies that are precise, quick, and conserve energy for real-time inter-user and device interaction. This paper outlines a new method of proximity detection, which employs both Bluetooth Low Energy (BLE) signal strength and inertial measurement unit

(IMU) sensor fusion to achieve higher levels of accuracy and stability in complex environments. Our approach aims to enhance detection accuracy while minimizing adverse impacts from signal fluctuations in wireless sensing, all while maintaining minimal processing requirements suitable for smart collaborative workspaces.

The methodology combines BLE Received Signal Strength Indicator (RSSI) measurements with IMU data, which includes an accelerometer and gyroscope, using a weighted fusion strategy. The proximity score P is calculated as:

$$P = \alpha \times S_{RSSI} + \beta \times S_{IMU} \quad (1)$$

In Equation (1):

- S_{RSSI} represents the normalized RSSI signal strength.
- S_{IMU} denotes the motion stability score derived from IMU data.
- α and β are weighting coefficients, constrained such that α + β = 1, allowing the system to balance reliance on signal quality versus motion context.

Equation (2) explains the procedure of adjusting the value of the RSSI (Received Signal Strength Indicator) to a specified interval from which it would be normalized to a range of [0,1].

$$S_{RSSI} = \frac{RSSI - RSSI_{min}}{RSSI_{max} - RSSI_{min}} \quad (2)$$

This form of normalization ensures that the raw RSSI values, which are influenced by environmental factors and hardware variations, are mapped within a defined minimum and maximum threshold. This technique particularly enhances the reliability and robustness of proximity estimation in heterogeneous smart environments, where devices and signal conditions are constantly changing, by standardizing the input range.

The inclusion of wireless signal metrics and motion context in the proposed methods form a highly accurate and adaptable proximity detection technique that is ideal for social active collaboration environments. The system combines distance estimation with the use of IMU-based motion signal analysis, which enables the redundancy of standalone signal-based approaches. The weighted fusion model in Equation (1) adjusts the weight of each data source in a selective manner according to the context. Equation (2) addresses the standardization of the input, specifically the RSSI, so that it can be used across different conditions. All these components form a robust framework that guarantees real-time performance under user presence detection and interaction with collaborative smart environments.

In the proposed methods, Figure 1 illustrates the steps from raw data collection to computing the proximity score, after which decision-making occurs. The flow contains BLE scanners that continuously fetch RSSI values from available devices. Simultaneously, IMU sensors fetch the accelerometer and gyroscope data. All of these data series, at a minimum, undergo filtering and normalization and then undergo fusion or merging. With each calculated score, a corresponding proximity score is also computed. This score responds to a limit that has a set value but changes over time, thereby determining the classification of proximity states and allowing users in collaborative applications to res

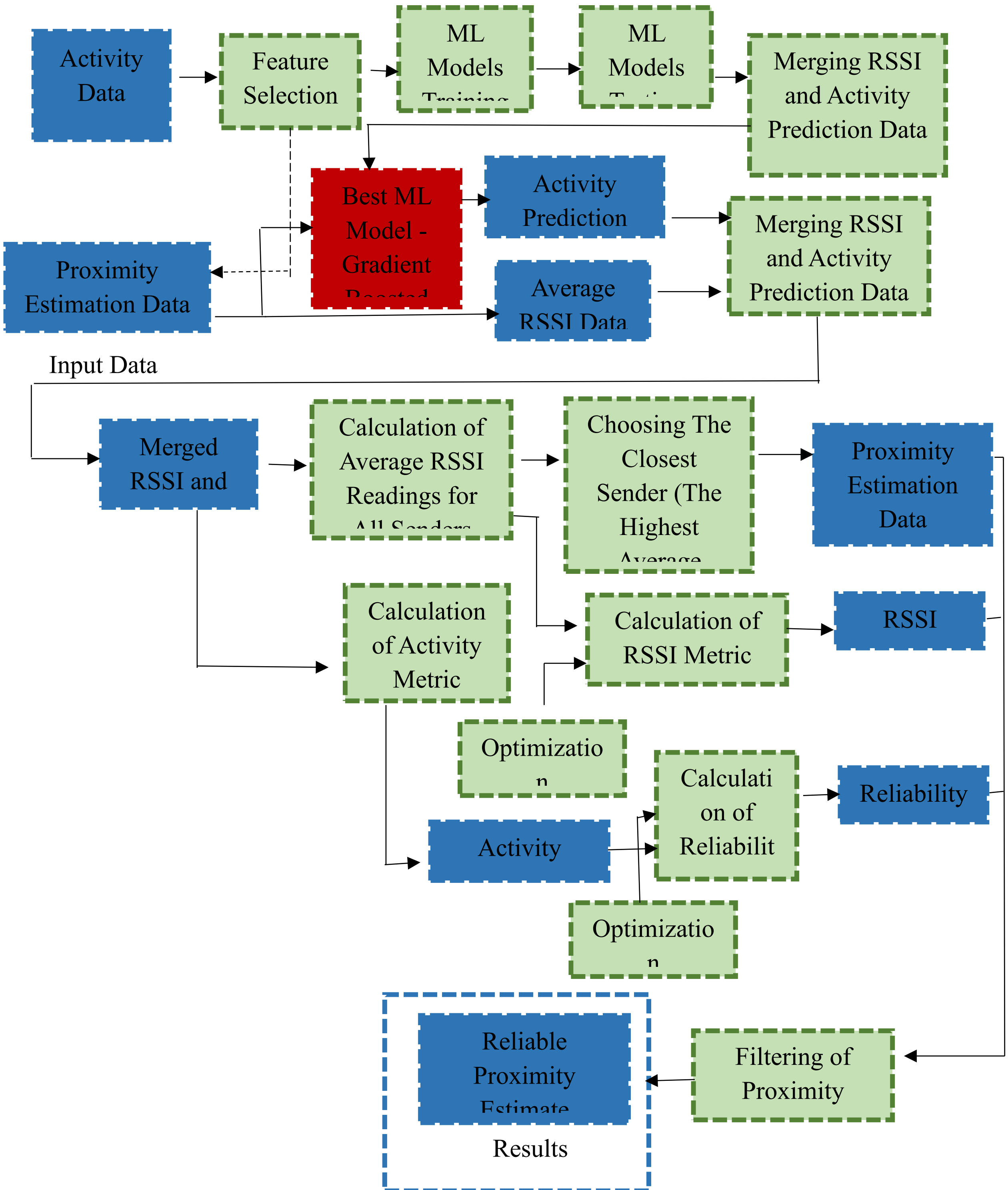

Figure 1: Hybrid Proximity Detection Flowchart

Figure 1 demonstrates the entire workflow of the hybrid proximity detection sub-system, which combines data from the BLE RSSI, IMU sensor, and machine learning to provide accurate proximity estimates. The first step involves collecting activity data and proximity estimation data, which are then processed through feature selection, model training, and evaluation using Gradient Boosted Trees. This model is utilized for real-time activity Prediction, which is performed alongside average RSSI values to create a dataset for proximity estimation.

The lower part of the flowchart showcases the sensor fusion layer, where IMU data is fused with RSSI information to estimate averages. The averages which are computed include the mean RSSI, activity metric, and RSSI metric. All of the above metrics are tuned for optimum performance. The system then estimates the radius of proximity by ascertaining the highest average RSSI, which further augments the proximity assessment. At the same time, an inactivity measure is computed by the reliability metric logic, which evaluates the consistency of RSSI and activity data over time. Before the metrics reach the filtering stage to eliminate weak or inconsistent outputs, all of the metrics are optimized. The estimate provided is referred to as an estimate of proximity. It is deemed reliable as it is protected against noise on the signal, jerky user motion, and environmental changes. The logic provides context-sensitive disparity detection while factoring in the collaborative needs for the set of environments. The flow demonstrates the downtime intention, which is intended to aid the system in achieving a faster signature response time.

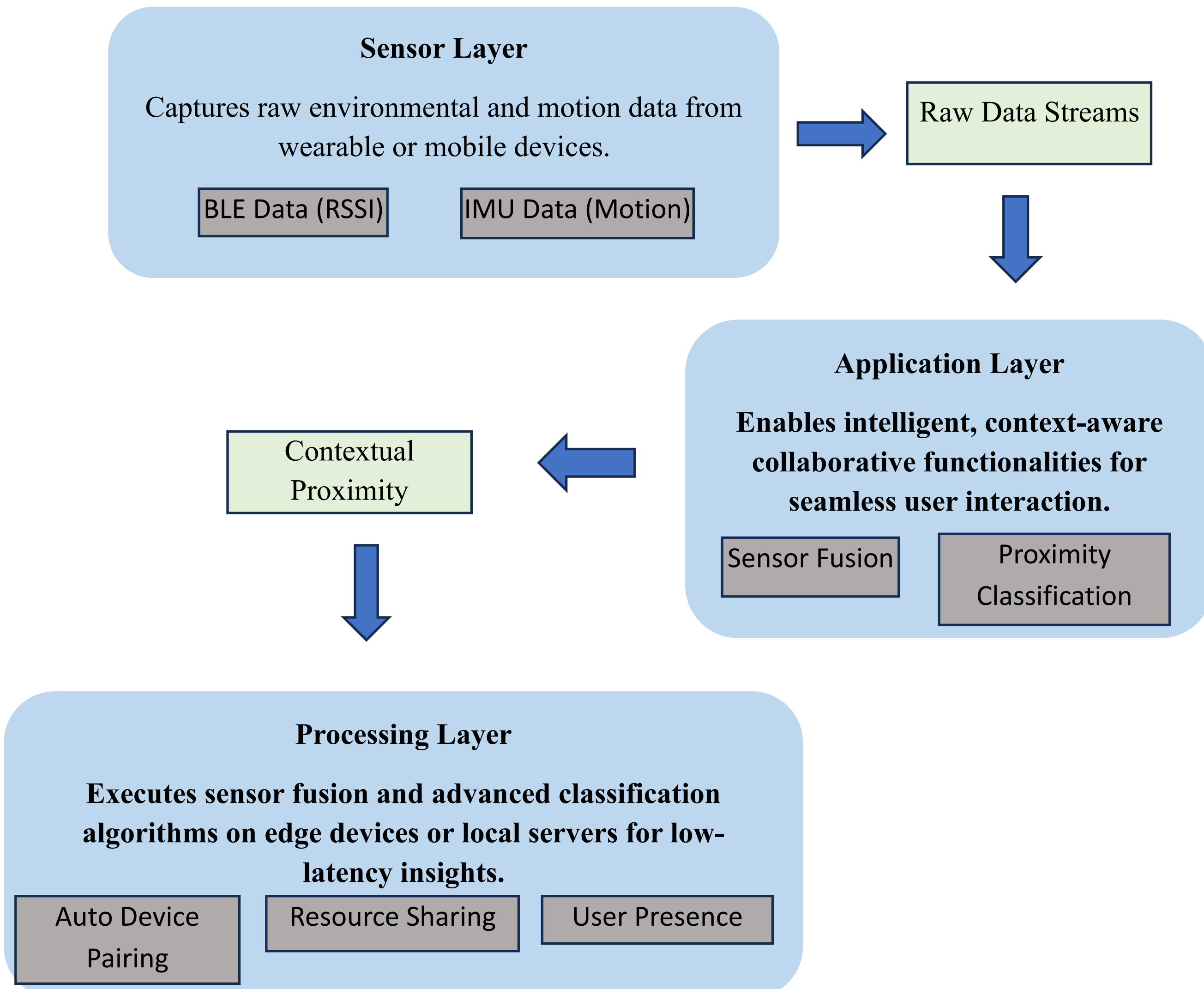

Figure 2: Proximity Detection System Architecture.

Figure 2 illustrates an example of a structured multilayer framework designed for processing sensor data, enabling intelligent and context-aware behaviors that facilitate interactions. This architecture is divided into three separate layers: the Sensor Layer, Application Layer, and Processing Layer. All of these layers exhibit a vertical hierarchy, with data progressing from its most basic form to more advanced forms, ultimately yielding insights. The process begins at the Sensor Layer where raw environmental data and motion data is captured. Emphasis is placed on collecting Bluetooth Low Energy (BLE) data, marked by Received Signal Strength Indicator (RSSI), as well as Inertial

Measurement Unit (IMU) data from motion generated by wearables or mobile devices. Such input results in "Raw Data Streams" which serve as the building blocks for the processing that follows.
After the steps involved in the initial data acquisition, the "Raw Data Streams" undergo processing in the functional block referred to as the Application Layer. This layer is crucial for the development of multi-layered, intelligent, context-aware, and collaborative interfaces that facilitate user interactions. Among others, the Application Layer performs "Sensor Fusion" and "Proximity Classification". It is reasonable to hypothesize that the data provided by several sensors is integrated and analyzed to establish relationships between proximity and context. The contextual proximity information, as presented above, is further utilized in the ultimate layer as its input. This layer is fed with contextual information and performs advanced sensor fusion and classification algorithms on edge devices or local servers. This framework supports the production of near real-time insights, which enables "Auto Device Pairing", "Resource Sharing", and "User Presence", as well as other experimental frameworks, where raw sensor data is transformed into actionable intelligence for user interaction.

IV. RESULTS AND DISCUSSION

The proposed hybrid proximity detection system was applied and tested in a configured smart workspace with ten mobile nodes featuring BLE and IMU sensors. These nodes simulated user-held or wearable devices in a collaborative environment. The tests included static positioning, walking, group clustering, and random motion at varying distances (0.5 m to 5 m). The system was tested in different environments with signal interference from Wi-Fi networks and physical interruptions from people. Detection accuracy, latency, and energy consumption, as well as efficiency, were the focus of evaluation, contrasting the hybrid approach with pure RSSI and IMU methods.

Table 1: Accuracy Comparison of Proximity Detection Techniques

Method	Accuracy (%)	Avg. Latency (ms)	Energy Consumption (mWh)
RSSI-Based Only	74.6	150	8.1
IMU-Based Only	79.3	90	6.7
Proposed Hybrid Method	91.2	95	7.3

Table 1 includes a comparison of the performance of the traditional proximity detection methods and the proposed hybrid method. The hybrid method outperformed both standalone RSSI and IMU techniques, reaching an accuracy of 91.2%, which is significantly greater. It also sustained low latency and moderate energy usage, further supporting its use in real-time ubiquitous collaborative systems. Incorporating motion context via IMU data helped stabilize detection during user movement, and normalizing RSSI mitigated the impact of signal variability, thereby enhancing system robustness.

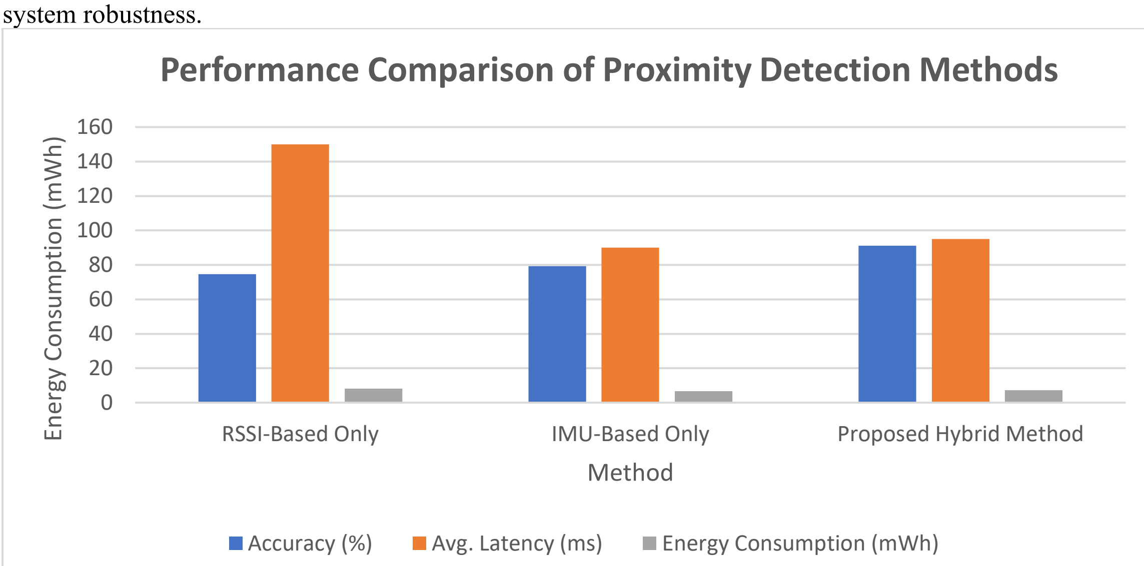

Figure 3: Performance Comparison of Proximity Detection Techniques

As shown in Figure 3, the accuracy, latency, and energy consumption of the three proximity detection methodsnamely, RSSI-Based Only, IMU-Based Only, and the Proposed Hybrid Method are evaluated. The Proposed Hybrid Method outperformed the RSSI-only and IMU-only approaches by considerable margins, achieving an accuracy of 91.2%, which is considerably higher than the RSSI-only's 74.6% and IMU-only's 79.3%. This illustrates the fact that fusing BLE RSSI measurements with IMU sensor data enhances the reliability of detection in dynamic collaborative settings. Regarding latency and energy consumption, the hybrid method exhibited the lowest average latency of 95 ms, which is comparable to the IMU-only method (90 ms) and outperforms the RSSI-only method (150 ms). The energy consumption was moderate at 7.3 mWh, which is a compromise between the higher consumption of RSSI-only at 8.1 mWh and the lower consumption of IMU-only at 6.7 mWh. These findings underscore that the hybrid approach provides an almost ideal balance of accuracy, responsiveness, and power requirements, ideal for real-time collaboration systems.

V. CONCLUSION

In conclusion, the novel approach of hybrid proximity detection utilizes both Bluetooth Low Energy (BLE) RSSI measurement techniques and Inertial Measurement Unit (IMU) sensors to enhance the accuracy and reliability of proximity sensing within collaborative contexts. Empirical data corroborates that the combined method achieves superior accuracy and efficiency when compared to using IMU or RSSI methods in isolation, concerning detection accuracy, reduced response time, and moderate power expenditure. With the aid of sensor fusion, the system mitigates the adverse effects of signal variation and user movement, which are common in dynamic scenarios. These improvements allow for enhanced responsiveness and more intuitive, context-sensitive user-device interactions. The proposed framework is also easy to scale and adapt, making it applicable in diverse smart ecosystems, such as offices, schools, and hospitals.

Along with these improvements, ensuring continuity of cross-device interaction without compromising user privacy, while also performing constant proximity detection, remains challenging. We aim to address these problems in the next phase of the research by utilizing advanced machine learning techniques, as well as edge computing and privacy protection approaches. This work strengthens the design of intelligent, user-driven collaboration systems that work reliably, seamlessly, and efficiently at scale, providing users with an enriched ubiquitous computing experience.

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