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Evaluation of Underfloor Accelerometers for Enabling Location-Based Services in Intelligent Environments

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Received: 8 November 2024 / Revised: 29 January 2026 / Accepted: 30 January 2026

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Abstract

Device-free indoor localization systems play a pivotal role in enhancing the functionality and intelligence of modern environments. They can effectively monitor people's movements in their everyday environment without the constraints of invasive or wearable devices, and are open to a wide range of application domains. Through a systematic experimental approach, in this work we investigate the performance of underfloor accelerometers in accurately detecting and tracking user movements. The collected data, augmented with ground truth information, are analyzed using fingerprint maps and k-Nearest Neighbor (k-NN) algorithms to estimate the user's position within the environment. In the literature, this work represents a first attempt to apply the fingerprint technique in this context. The results show promising capabilities of underfloor accelerometers in facilitating location-based services, while the short time required for installation, data pre-processing and calibration indicate this approach as an easy-to-deploy location-based system. In this regard, intra-user tests show that the variability of the error exceeds 1 m regardless of k-values or time windows, inter-user tests show that the time window does not affect the variability of distance estimation with 2-NN, which outperforms other k-configurations, while 3-NN performs better as the time window increases. The cumulative distribution function over the entire test set shows that more than 75% of the predictions are less than 1 m.

Keywords Indoor localization system · Infrastructure-based positioning · K-NN · Location-based services · Device-free localization

1 Introduction

The seamless integration of technology into our surroundings promises to revolutionize the way we interact with our environments. A fundamental aspect of this advancement lies in the accurate location of individuals within indoor spaces and the provision of location-based services tailored to their needs. This is particularly crucial for applications such as room occupancy detection and walk tracking, which underpin various sectors, including smart buildings, healthcare, retail, hospitality, and entertainment [1].

Indoor localization systems have emerged as indispensable tools in this context, offering precise tracking capabilities within confined spaces where GPS signals may be unreliable or unavailable. These systems take advantage of a myriad of technologies, ranging from Radio Frequency Identification (RFID) and Bluetooth beacons



to Wi-Fi fingerprinting, ultrasonic sensors, and computer vision [2]. Their implementation not only improves the efficient management of spaces but also provides context-sensitive services, thereby enhancing user experience and operational efficiency [3]. Furthermore, the application domain of location-based services extends far beyond mere technical capability, encompassing a wide spectrum of domains and applications. In healthcare, for example, location-based services facilitate real-time asset tracking, patient monitoring, and workflow optimization, leading to improved clinical outcomes and operational efficiency. Similarly, in retail environments, personalized recommendations, targeted advertising, and foot traffic analysis leverage indoor localization data to increase customer engagement, drive sales, and optimize store layouts. In addition, in hospitality settings, indoor localization allows seamless guest experiences, efficient staff management, and personalized services, enhancing overall guest satisfaction and loyalty. This holistic perspective underscores the diverse ways in which location-based services enrich daily lives and redefine human-computer interaction [4, 5].

In this context, fingerprint applications based on conductive floors represent a standard approach in location-based services [6]. By analyzing the distinctive capacitance patterns generated by individuals' footsteps, these systems can create unique "footprint" profiles akin to fingerprints, facilitating robust and reliable localization in diverse environments. Furthermore, the non-intrusive nature of conductive floors ensures user privacy and comfort, making them an attractive solution for a wide range of indoor applications.

Intelligent floors have garnered significant attention among the wide range of indoor localization technologies due to their potential to revolutionize the field. [7]. These innovative flooring systems use capacitance sensors embedded in floor panels to detect capacitance variations caused by the presence and movement of people. By exploiting the unique capacitance patterns generated by individuals' footsteps, these systems can discern not only the presence, but also the identity and behavior of occupants within a space. Such fine-grained localization capabilities enable a plethora of applications, from personalized navigation and targeted advertising to enhanced security and energy management. Capacitive floors can be susceptible to environmental interference, such as changes in humidity or electromagnetic noise from nearby electronic devices. These factors can affect the accuracy and reliability of the localization data they provide. Additionally, the material of the floor tiles can influence how signals propagate, making it an important consideration when installing data collection systems to ensure optimal performance. In this paper, we propose an indoor localization system based on accelerometers, which are less affected by environmental factors and provide reliable motion detection across varying conditions, though occasional calibration and maintenance may still be necessary to ensure optimal performance. Calibration is necessary to account for changes in capacitance sensitivity over time and variations in environmental conditions. In contrast, accelerometers typically require minimal calibration and maintenance, making them more convenient for long-term use. Capacitive floors excel in static indoor environments, providing precise location and occupancy detection within confined spaces. However, accelerometers thrive in dynamic environments, offering continuous motion tracking and orientation detection on mobile and wearable devices. By understanding these differences and harnessing the strengths of each technology, researchers and practitioners can unlock new opportunities to create location-based services that seamlessly integrate with our daily lives.

This work has been partially inspired by [8] that exploits accelerometers to monitor a historic masonry tower for structural health monitoring purposes. Along with the indoor location system based on underfloor accelerometers, we propose a fingerprinting technique to obtain positioning estimates.

Our methodology is intended to deliver a seamless, unobtrusive indoor localization framework, tailored for settings in which wearable devices or user-bound technologies are impractical, undesirable, or logistically difficult to deploy. The core of the approach is a flooring infrastructure composed of sensor-equipped tiles that enables location-based services without requiring individuals to carry any additional hardware, install applications, or actively interact with the system. By eliminating the dependency on personal devices, the system supports a device-free localization paradigm. This characteristic is particularly advantageous in temporary or semi-permanent venues, such as museums, hospitals, or exhibition halls, where operators seek to enhance visitor engagement, analyze crowd flows, and optimize spatial design, yet wish to avoid the overhead associated with complex installations, maintenance of loaned equipment, or mandatory user registration. Moreover, the minimal

visual and physical footprint of the embedded tiles maintains the aesthetic and functional integrity of the environment. Because the sensing components are integrated directly into the flooring, they remain effectively invisible to visitors, thereby preserving the natural experience of the space and avoiding any perception of surveillance or technological intrusion. Spaces that undergo frequent layout changes, rotating exhibitions, or periodic restructuring could adapt to the system with limited effort, reusing or relocating tiles as needed.

The feasibility of using accelerometers is based on the accuracy of a specific calibration and their insensitivity to environmental conditions (e.g., humidity). Furthermore, the fingerprinting technique is a general method that can be used for every kind of data. Usually, this technique is used in the indoor localization domain analyzing the receiving signal strength. In this work, we applied a fingerprint technique and k-NN to estimate the user position, thus avoiding the need for a large dataset for training purposes. By combining fingerprinting strategy and accelerometer technology, our system proposes a novel approach to device-free indoor localization that is robust, accurate, and adaptable to diverse indoor environments. As a final contribution, we release the raw data collected and the Python code used in this paper as open source code, licensed under the CC-by-4.0 license on the Zenodo platform,¹ allowing in this way further research and development in the field of indoor localization.

According to the current state of the art in the field [9], no one in the indoor localization landscape has attempted to use underfloor accelerometers for a device-free indoor localization system, nor shared the code to allow readers to reproduce the results obtained according to the FAIR (Findability, Accessibility, Interoperability, and Reusability) principles. In summary, the main contributions of this work are as follows:

- Introduction of a novel device-free indoor localization system based on underfloor accelerometers, fingerprinting, and k-NN techniques.
- Release of the dataset collected from the installation of the system in a laboratory environment.
- Open access to the code developed for data pre-processing, result generation, and plot creation.

The remainder of the paper is structured as follows: Sect. 2 presents related work; Sect. 3 provides a detailed description of the proposed system, including the methodology and data collection pipeline; Sect. 4 discusses the results, covering experimental settings, evaluation, and a comparison of k-NN implementations for intra- and inter-user testing; Sect. 5 concludes with comments and insights for future research directions.

2 Related Work

In 2021, Alam et al. [10] present a review of non-RF techniques for unobtrusive indoor localization. Among the different types of technologies considered, higher accuracy is reached by deploying specific high-cost sensors such as vision/camera, infrared, and visible light. They also analyse sensors based on physical excitation (i.e., pressure and vibration) and based on an electric field (i.e., capacitive and passive). This work relies on vibration sensors, and in this section, we highlight strengths and weaknesses considering both the electric field and physical excitation. We suggest a reading of [11] for an in-depth analysis of capacitive sensing in human-computer interactions.

Electric field sensing is based on detecting variations in capacitive coupling. The process in which an external user produces variations in the transmitter electric field is often called capacitive sensing. Otherwise, the process in which the electric field alterations are the consequence of user movements and no transmitter is required is usually referred to as passive sensing.

In 2012, [7] introduced flexible and integrated capacitive sensitive solution based on free hardware, accessible, allowing for indoor location and fall detection, specially designed to address the challenges of the Ambient Assisted Living (AAL) environment. In their proposal, the system consists of sensors mounted on various types of floor covering, wirelessly transmitting data to the central platform, and providing location and fall detection

¹ <https://doi.org/10.5281/zenodo.10838489>

services to the associated AAL platform. Despite their good accuracy, capacitive sensors require proper calibration, and to achieve such high accuracy, a fine-grained drift compensation is required as well. During the international competition of EVAAL, its system achieved a location accuracy of 50 cm.

Lauterbach et al. in [12] proposed a large-scale textile-based sensor system, installed below the floor, capable of detecting people moving on the ground and calculating their trajectories. However, their deployment required 4 radio modules and 32 sensor areas per square meter.

In [13], the authors describe the performance obtained by machine learning classifiers in an indoor location scenario with capacitive sensors. In their paper, the authors compare the performance of the Weka collection ML classifier using experimental data from an indoor human positioning system based on capacitive sensors in a 9-square-meter room. Their results show a large variance between algorithms and, in some cases, they obtain remarkable results. However, their approach requires an extensive dataset for training and validation to obtain high accuracy.

In summary, systems based on electric field recognition may exhibit excellent performance. The strengths of these approaches are based on the unique property of capacitive sensors that can be prototyped with common materials and are generally produced and available at a low cost. Furthermore, this kind of sensor is exclusively electrical and requires low power. Nevertheless, they require a dense array of sensors for optimal functionality or a robust data collection process to create a training dataset suitable for more advanced artificial intelligence models.

Similarly to the above-mentioned approaches, if we consider the physical excitation and the interaction of a person who moves into an environment as the trigger event for sensing, the position of this person can be evaluated by estimating the source of the excitation. For example, a person who moves his or her footsteps over an intelligent floor can be passively localized step by step using the contact of his or her foot with the floor. This approach can be followed using pressure and/or vibration sensors.

In [14], the authors show a 0.6 m \times 0.6 m tile with a load cell placed in the middle. The authors performed an experimental evaluation by placing 25 tiles separated by 0.2 m just below a wooden floor on a 5 m \times 5 m grid. By analyzing the raw data using a Kalman filter and a probabilistic data association (PDA), they obtain an error of 0.28 m for 85-percentile tracking of a single target on a portion of the experimental scenario. Also in [15] the authors experience the identification of falls of older people in apartments using force sensors and three-axis accelerometers hidden within smart floor tiles. Their floor sensor prototype consists of 104 tiles (60x60 cm), and each tile is equipped with a 3-axis accelerometer in the center of the tile and four force sensors positioned at each corner. The focus here is on detecting the posture of the monitored person (e.g., walking, sitting, standing). However, these systems start from the assumption that the entire floor must be covered with the proposed tiles, making its use impractical.

Moving from hardware choices to data analysis techniques, in this paper, we test our system by implementing a fingerprint technique, estimating user positions by applying a k-NN algorithm [16]. We suggest reading [17] for an extensive discussion on the fingerprint technique applied in the indoor localization scenario, but in the following we will briefly report the main characteristics.

Fingerprinting techniques are commonly used in indoor localization systems to determine the location of a user or device within a circumscribed indoor space. This technique relies on creating a database (aka a fingerprint map) of signal characteristics from different access points or sensors within the indoor environment. Fingerprinting techniques offer several advantages for indoor localization, such as high accuracy and flexibility. High accuracy strongly depends on a well-constructed fingerprint database and its ability to represent different measurements. Fingerprinting also shows great flexibility because this technique can be applied to various types of signal and sensor, making it adaptable to different indoor environments and use cases.

This technique also has some limitations. For example, the initial setup cost cannot be negligible. In fact, creating a fingerprint database may require extensive site surveys and signal measurements. In this paper, we create a fingerprint database using ground-truth measurements (see the next section for more details). The fingerprint approach could also contribute to an increase in system maintenance overhead. In fact, the exploitation of radio

signals can lead to the need for a periodic update to reflect changes in the indoor environment, such as renovations or obstructions. This particular problem may be greatly mitigated if the technique is applied to accelerometers placed on the floor.

In general, fingerprinting techniques play a crucial role in indoor localization systems, offering a robust solution to accurately determine locations within complex indoor environments. To the best of our knowledge, this work is the first to introduce the fingerprint technique, which is generally proposed for radio signals, for accelerometers to achieve intelligent floors.

Moreover, the proposed solution, leveraging accelerometer technology, is agnostic to environmental interference, such as changes in humidity or electromagnetic noise, and does not require regular calibration or maintenance to ensure optimal performance, as is typically necessary for capacitive sensors. Furthermore, compared to the state of the art, our approach does not require covering entire floors with sensorized tiles; a limited number of the proposed devices is sufficient to localize users.

3 Proposed System and Data Collection Pipeline

Data collection is carried out in an environment where 8 accelerometers are placed under floor tiles, as shown in Fig. 1, and arranged as an 8x3 matrix. The sensors are installed, equally spaced, in two parallel alternating columns of tiles, separated by a third column of tiles without sensors. Each tile size is 60x60 cm. To optimize sensitivity and eliminate the need for post-processing calibration, sensors were positioned at the center of each tile, where bending is naturally most pronounced due to the lack of the floor support structure. This strategic placement amplified the sensors' response to applied pressure and enhanced data quality. The sensing units used are based on the high-performance triaxial LIS344-ALH inertial sensor manufactured by STMicroelectronics, which is capable of measuring accelerations over a maximum bandwidth of 1.8 kHz along all axes (X/Y/Z) with a selectable full scale of ± 2 g/ ± 6 g.

A block diagram of the main components of the system is presented in Fig. 2. Each of the eight accelerometers is directly connected to a Raspberry Pi board and outputs three analog voltages, one for each of the axes, proportional to the linear acceleration detected. To acquire the acceleration data from the sensors, the analog signals are converted to digital values using Microchip MCP3424 analogue-to-digital converters (ADCs) running at about 70 samples/second. A data logging service running on the Raspberry Pi is able to both store the information locally or transmit the readings in real-time to a data storage server via an MQTT broker. The MQTT protocol was chosen for its speed and scalability, which allows easy integration of additional acquisition units in the future. The data storage also collects environmental camera recordings. The data processing module first generates a fingerprint map using data from both the accelerometers and the camera. Subsequently, it estimates the user's position by combining the fingerprint map with accelerometer data collected from the floor.

Fig. 1 Picture of the experimental setup showing an accelerometer sensor attached to a floor tile and connected to the data collector device

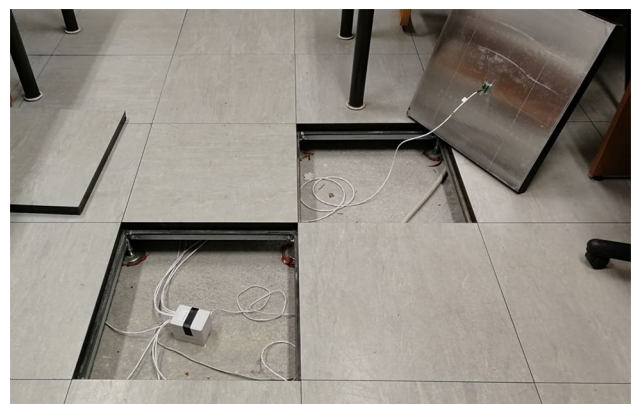
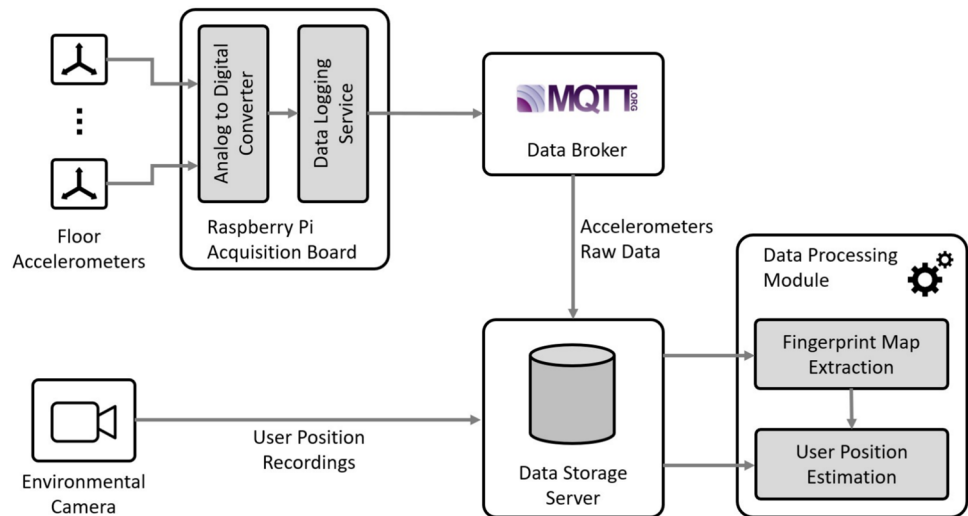


Fig. 2 Block diagram showing the layout of the main system components



3.1 Methodology

As part of a feasibility-driven system-validation study, three distinct walking paths were executed by two participants, during which video recordings, accelerometer measurements, and corresponding ground-truth and fingerprint maps were collected. The study was designed around the central research question of whether floor-borne vibration signals, captured through the proposed accelerometer configuration, contain sufficient spatial information to support location-based services under realistic walking conditions. Because step-induced vibrations are primarily governed by the mechanical interaction between the foot and the floor, the magnitude of the excitation force, and sensor sensitivity, the two participants were deliberately chosen to be different in height, weight, and overall body characteristics. This intentional contrast was introduced to evaluate different excitation forces and gait dynamics, thereby enabling assessment of whether the sensing and processing pipeline remains consistent. Although this setup does not permit statistical generalization to a broad population, the performance observed across these cases supports the level of generalizability claimed in this work, namely the feasibility of vibration-based indoor localization using minimal instrumentation.

To annotate the ground truth, we utilized an indoor camera mounted on a wall to record the experiment, capturing the trajectories of each user on the sensorized floor and providing precise positional data. To ensure precise synchronization between the timestamps of the Raspberry Pi and the camera, we used a control signal generated at the beginning of each test session, complemented by the use of the network time protocol for accurate alignment. Specifically, for each coordinate point in the monitored area, a unique "fingerprint" is created from the readings of all deployed sensors. These readings vary based on the user's proximity to each sensor, with higher values for sensors closer to the user and lower values for sensors farther away. The resulting fingerprint map associates each coordinate point to the corresponding set of sensor readings.

To account for random walking patterns, we designed our dataset with three different paths, given the spatial constraints of our lab. These include two circular paths of different lengths, where the user walks directly over the sensors, and a third path with two deviations along a straight line, where the user walks near, but not directly over, the sensors. While not exhaustive, this setup approximates a range of realistic movements, balancing environmental constraints with the need for representative data.

Figure 3 illustrates the pipeline followed in this study. Specifically, to generate the fingerprint map, we synchronize the ground truth positions recorded by the camera with the sensor readings from the accelerometers, ensuring their alignment with the timestamps provided by the camera. To achieve precise synchronization of the camera and accelerometer recordings, a brief impact with the floor is generated at the start of each experiment,

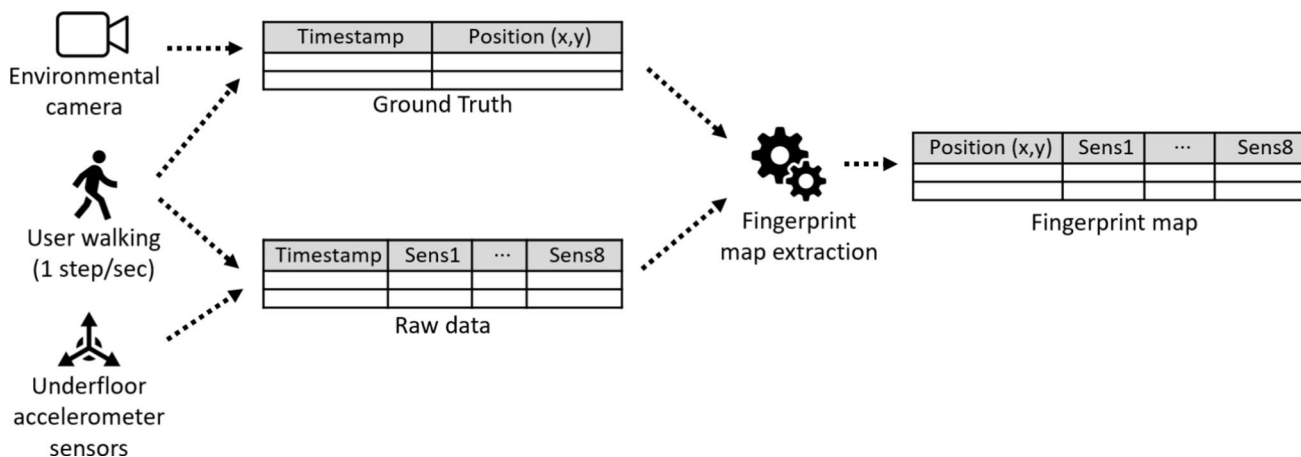


Fig. 3 Workflow of the fingerprint map generation

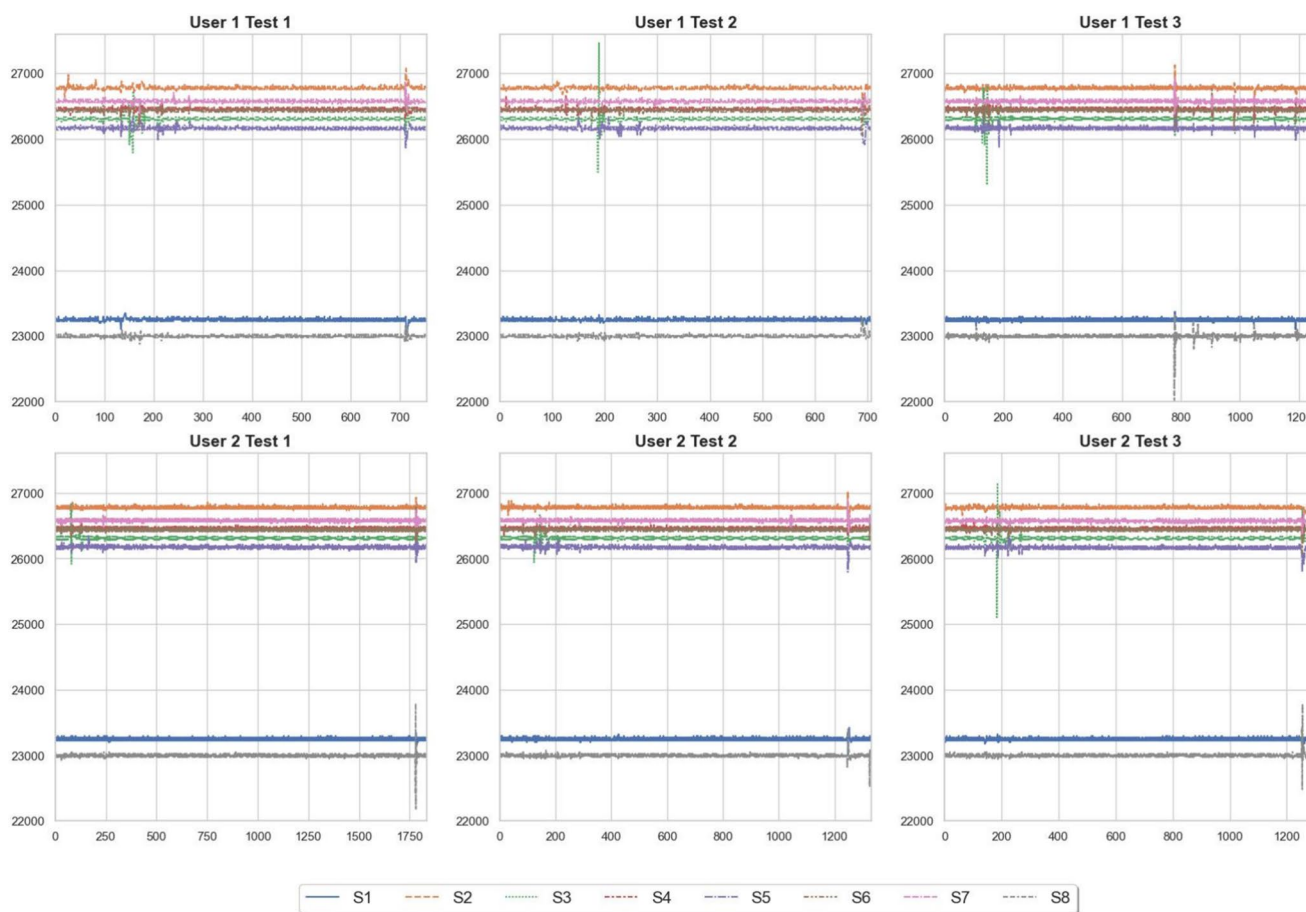


Fig. 4 Raw values captured by the accelerometers without user presence

strong enough to be detected by both the accelerometers and the camera microphone. This common event is used to ensure a precise temporal alignment of the tracks.

Given that the collected data consists of signals returned by accelerometers, we note that each sensor, when no one is in the room, has a different value, as illustrated in Fig. 4. Even when unloaded, each sensor reports distinct

acceleration readings. This discrepancy underscores the need for careful pre-processing and calibration of the data to ensure accurate analysis and interpretation. It should be noted that the sensors in the system have not been individually calibrated. Instead, the data management algorithm includes a pre-processing phase to characterize background noise and sensor responses in the absence of steps.

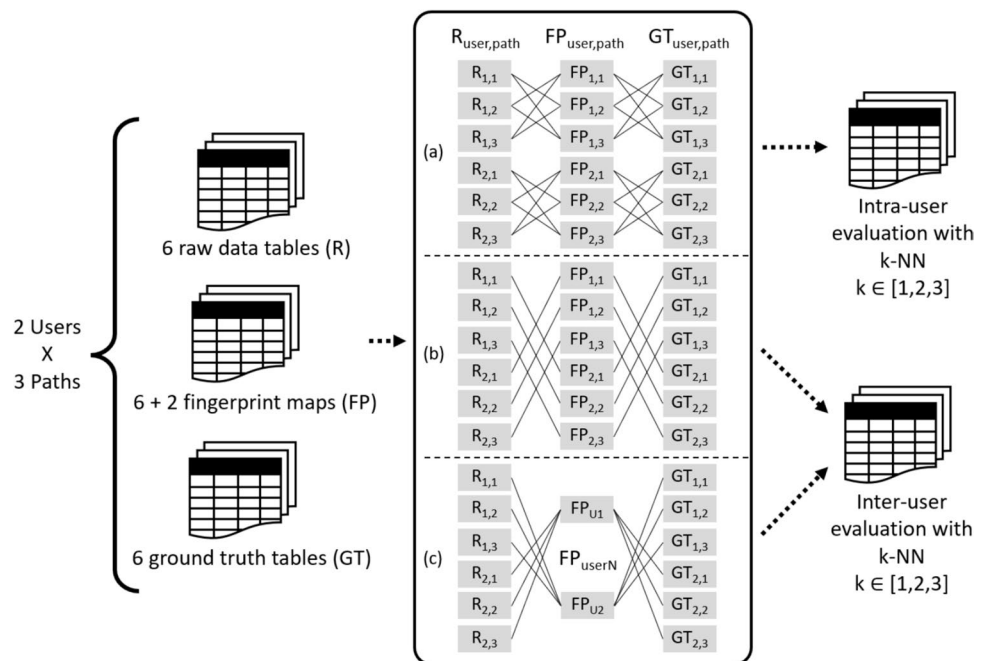
We eliminate this offset by subtracting the information collected by each sensor during each test from the average information collected by the same sensor before the start of the test, that is, when the user is not present in the room. Moreover, although acceleration data is recorded along all three axes for each sensor, only the data from the z-axis is selected during the pre-processing phase, as this axis is perpendicular to the floor and proves to be the most effective for detecting the user’s steps. This transformation yields a ready-to-process dataset.

The subsequent step involves creating fingerprint maps for all tests performed by each user. This process necessitates the presence of the ground truth dataset, which comprises information known to be real due to direct observation during the collection phase.

Figure 5 illustrates our approach of generating eight fingerprinting maps: one for each path and each user, and two additional maps for each user independent of the paths. This strategy enables the assessment of the generalisability of our system and the fingerprinting technique in various scenarios by amalgamating different maps from different users.

Subsequently, we conduct numerous intra- and inter-user evaluations. For each evaluation, we compute the n-dimensional distance between observations (i.e., raw data tables) and each entry of the fingerprinting maps over predefined time windows. The entry with the minimum distance determines the estimated position. The Euclidean error between this estimated position and the ground truth coordinates is then calculated to represent the localization error. A detailed description of all the intra- and inter-user experiments (blocks a), b), and c) in Fig. 5) is provided in Sect. 4.1.

Fig. 5 Intra- and inter-user evaluation approach



4 Results

In this section, we provide a detailed overview of both the experimental environment and the utilized setup, as well as the results obtained, focusing on analyzing the localization errors observed in each conducted test. We will examine the data collection process that involves two users across three different paths in the experimental environment. These paths include a rectangular path, a shorter rectangular path, and a 'chicane' path where users tread on specific sensors at the beginning and end while passing through others. Subsequently, we will discuss the specifics of data collection, the experimental setup, evaluation procedures, and finally, the results obtained, analyzing localization errors in various test contexts, both intra- and inter-user.

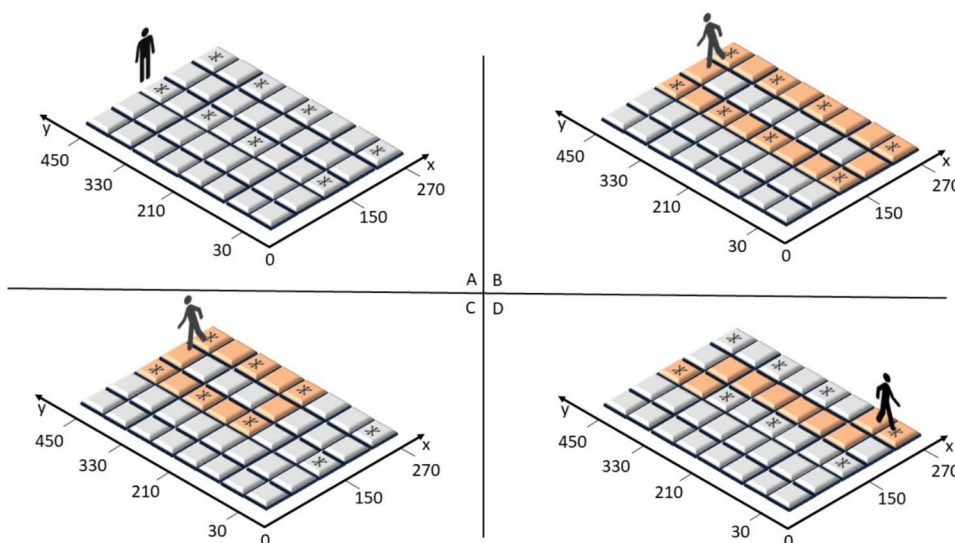
4.1 Experimental Setting and Evaluation

Data collection involves two users following three different paths in the environment. The first is a rectangular path (8x3 tiles) on which users walk over each sensor at least once. The second is a shorter rectangular path (5x3 tiles) on which users do not walk over the sensors at the end of the room. The third path is a 'chicane' path, on which users touch part of the initial sensors, part of the final ones, and pass between the others. Figure 6 shows all the paths followed by the two users. Specifically, sub-figure A shows where a user starts each path (note that the tiles equipped with the accelerometer are marked with a special icon), while sub-figures B,C, and D, respectively, show the three performed paths, that is: the rectangular path, the short rectangular path, and the chicane. In the remainder of the paper, these three paths are named p1, p2, and p3.

The two users involved in the experimental campaign are two males with different heights and weights, enriching the different steps, in terms of forces, that they produce on the floor. The two users are named u1 and u2, respectively.

To estimate the position of the user, we calculated the distance between the observations and each entry on the fingerprint map using the k-NN model [18]. With the data collected, we performed several tests by varying the value of k and slicing the datasets in different time windows. Moreover, we did not limit ourselves to the simple analysis of the base case, i.e., the estimation of positions over raw data using the respective fingerprint maps, but we performed tests on intra- and inter-user cases, as well as one-to-one cross-user predictions taking advantage of enhanced fingerprint maps (Fig. 5). Specifically, we consider k values spanning from one to three (i.e., $k = [1, 2, 3]$) and time window widths of ten, thirty, and sixty samples (i.e., $tw = [10, 30, 60]$). As shown in block (a) of Fig. 5, the intra-user tests consist of the following setups: User 1's first path estimates are evaluated

Fig. 6 The pathways among underfloor sensors. Tiles with sensors are marked with the accelerometer icon



using fingerprint maps generated from user 1's second and third paths; user 1's second path estimates are evaluated using fingerprint maps generated from paths one and three; and user 1's third path estimates are evaluated using fingerprint maps generated from paths one and two. With the same approach, identical estimates are made for user 2's paths.

However, the inter-user tests, shown in the block (b) of Fig. 5, consist of the following steps: estimating the position of user 1 in the first, second and third paths using the fingerprint maps of user 2 for the first, second, and third paths, respectively. Similarly, estimating the position of user 2 on the first, second, and third paths requires using the fingerprint maps of user 1 for the first, second, and third paths, respectively.

Additionally, we perform inter-user tests by estimating the positions for each of the three paths taken by user 1 through the aggregate of user 2's fingerprint maps, and vice versa as shown in block (c) of Fig. 5. Finally, for the sake of transparency and to make it easier for readers to reproduce the tests, we have made the code available via a Zenodo repository (see the above footnote).

4.2 Comparison of k-NN Implementations for Intra-User Tests

Intra-user testing entails forecasting a user's location based on their position data along a specified path, utilizing a fingerprint generated from the ground truth of a different path performed by the same user. Figures 7 and 8 show the error distributions obtained by computing the intra-user distance estimation for user 1 and user 2, respectively, in the three pathways.

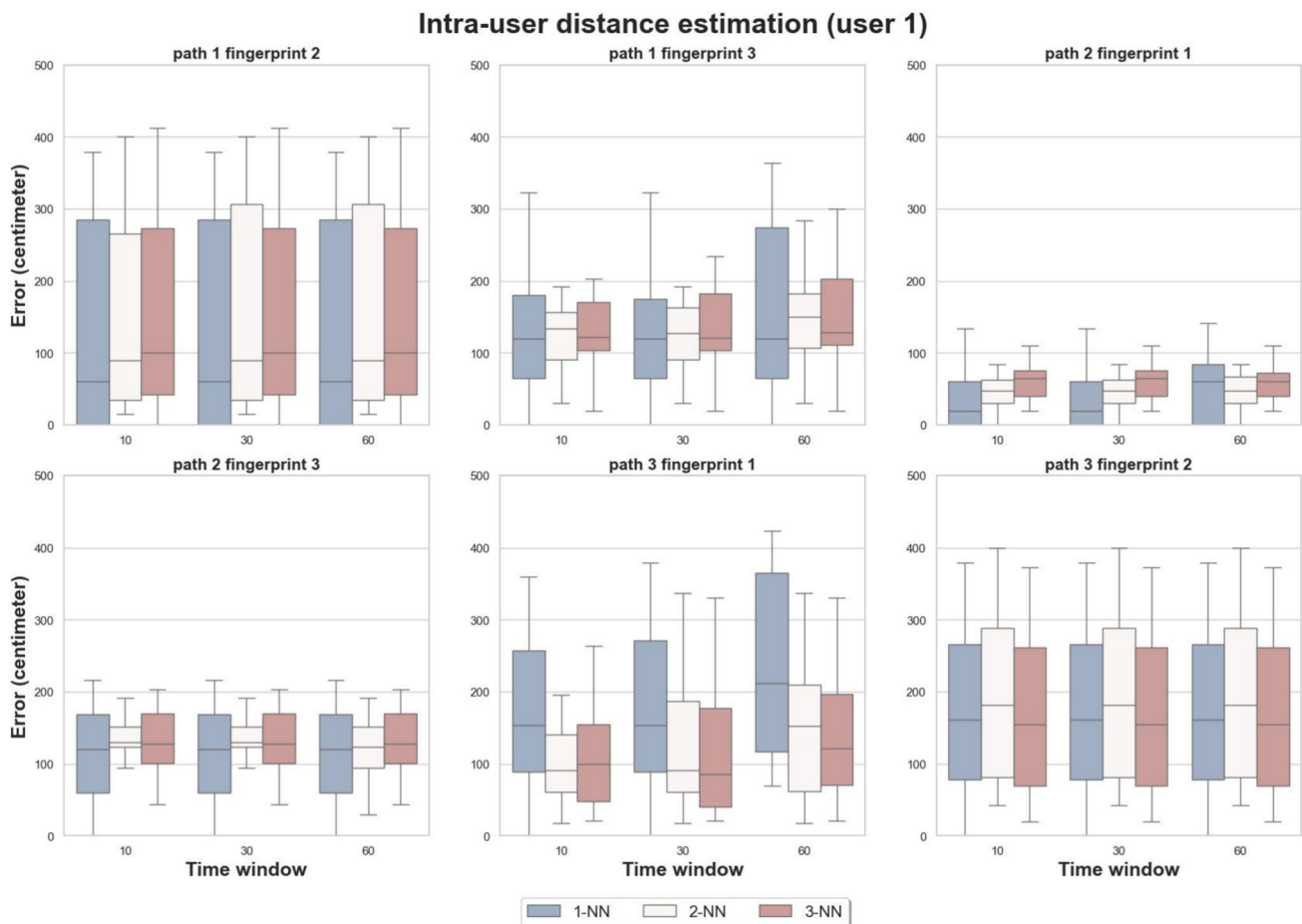


Fig. 7 Intra-user distance estimation distribution results for user 1

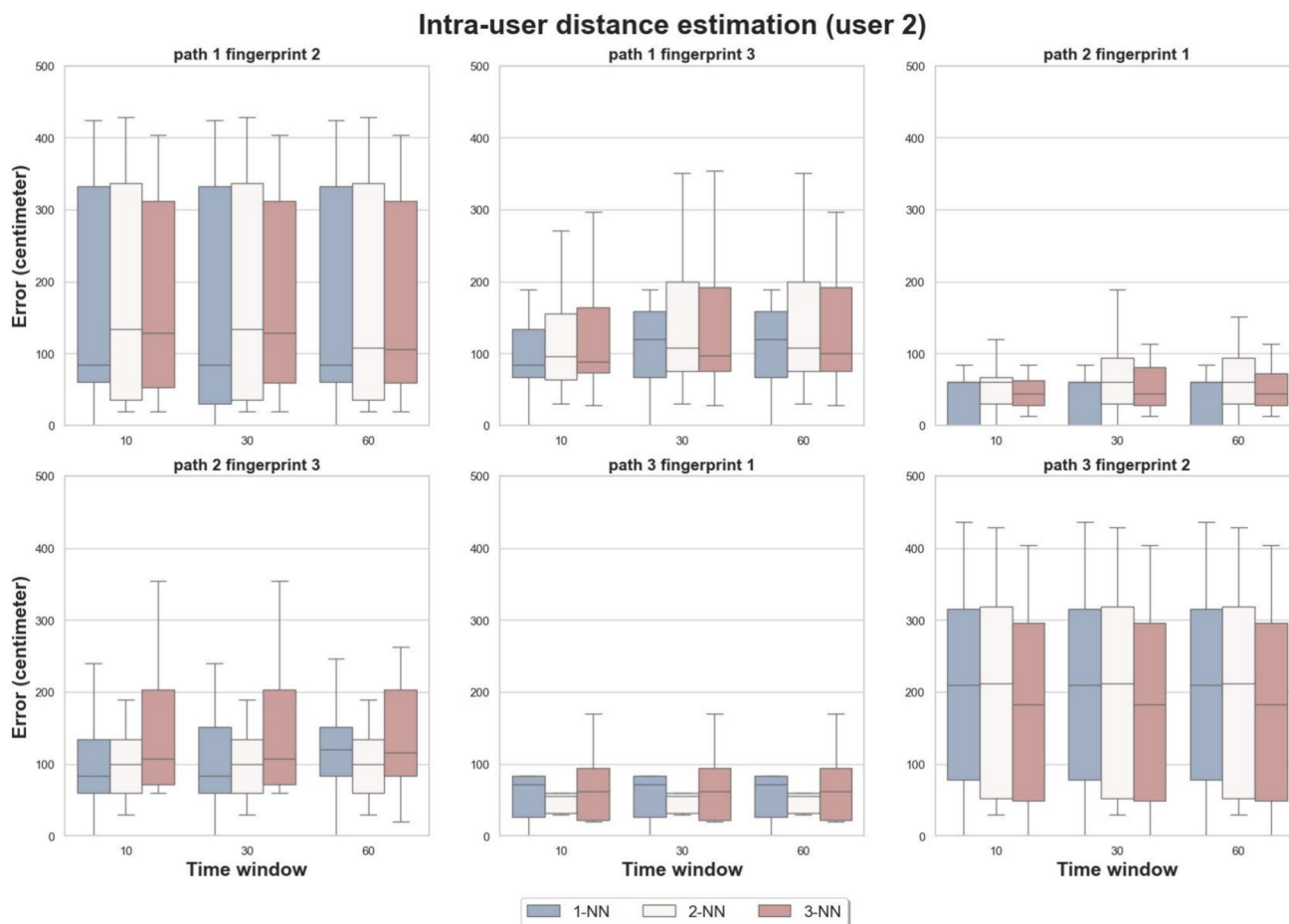


Fig. 8 Intra-user distance estimation distribution results for user 2

We note that the variability of the error is more pronounced, regardless of differing k values or time windows, when making predictions on paths with fingerprint maps that do not cover the whole sensorized environment (e.g., path 1, which reaches all sensors in a rectangle, evaluated with the fingerprint map constructed from the ground truth of path 2, which involves a more circumscribed rectangle with two of the eight sensors excluded from the path). Similar results are obtained when the positions of path 3 are estimated using the fingerprint maps obtained from path 2. In both cases, between the 25th and 75th percentiles, the average error ranges from a minimum of half a meter to more than 3 m. This trend is reversed when, on the contrary, we estimate the user’s position in a given path using fingerprint maps created from the ground truth that incorporates the considered path into a larger path (see path 2 with fingerprint 1 or path 3 with fingerprint 1 for both users). Due to the extensive data available for prediction, the latter also exhibits the lowest errors in distance estimation. Furthermore, it should be noted that the dimension of the time window does not affect the variability of the distance estimation with the 2-NN, which here gives the best performance compared to the other configurations of k , while the 3-NN results in the best compromise as the time window increases in both cases. This trend will become even more evident when discussing the outcomes of inter-user estimates, especially for those performed using enhanced fingerprint maps.

The most significant differences when looking at the distributions of the two users are in the evaluation of the third path (i.e., the chicane) with the fingerprint map based on the first. In this scenario, the distributions related to user 1 exhibit increased variability and a higher mean error. These variances predominantly stem from the physical differences between users, notably the thinner build of the first user compared to the second. This aspect becomes more evident when the path runs between the sensors and does not involve passing over them.

To better quantitatively assess the results obtained, we show the error distribution as k varies and the average error on a scale of 0 to 100 for each of the above configurations. To enhance the readability of the graphs, we applied min-max normalization to the average error result. Figure 9 shows the normalized average error for combinations of both user paths for each configuration of k as the time window varies. We note that the worst performance occurs when trying to make predictions with restricted fingerprint maps, while the lowest average error occurs when, on the contrary, estimates are made using all-encompassing fingerprint maps, especially those derived from the first path. The figure shows even more clearly how the average error decreases with increasing k when considering larger time windows.

4.3 Comparison of k -NN Implementations for Inter-User Tests

As above, the inter-user tests encompass two estimation strategies: i) one-to-one position estimation, which involves estimating the position of a user based on the fingerprint map of another user (Fig. 10), and ii) fingerprint-enhanced position estimation, which involves estimating the position of a user by utilizing the fingerprint map containing the comprehensive path information of another user (Fig. 11).

The box plots in the first row of Fig. 10 (one-to-one position estimation) show the distributions to estimate the position of user 1 in the first, second, and third paths, respectively, using the first, second, and third fingerprint maps of user 2. In contrast, the plots in the second row show the distributions for estimating the position of user 2 in the first, second, and third paths, respectively, using the first, second, and third fingerprint maps of user 1.

The most accurate estimates are observed within the median path, which incorporates the over-tracking of six out of the eight deployed sensors, omitting those that pose challenges in information collection due to the spatial layout of the laboratory. In fact, the latter proved to be more problematic in terms of information collection, given their proximity to certain workstations (with desks, chairs, etc.), which rendered them less sensitive to floor vibration propagation and more prone to signal distortion. The distributions with the greatest dispersion of values



Fig. 9 Normalized average error for intra-user tests. Each circular bar plot represents the average error percentage for three types of tests, categorized based on the time window

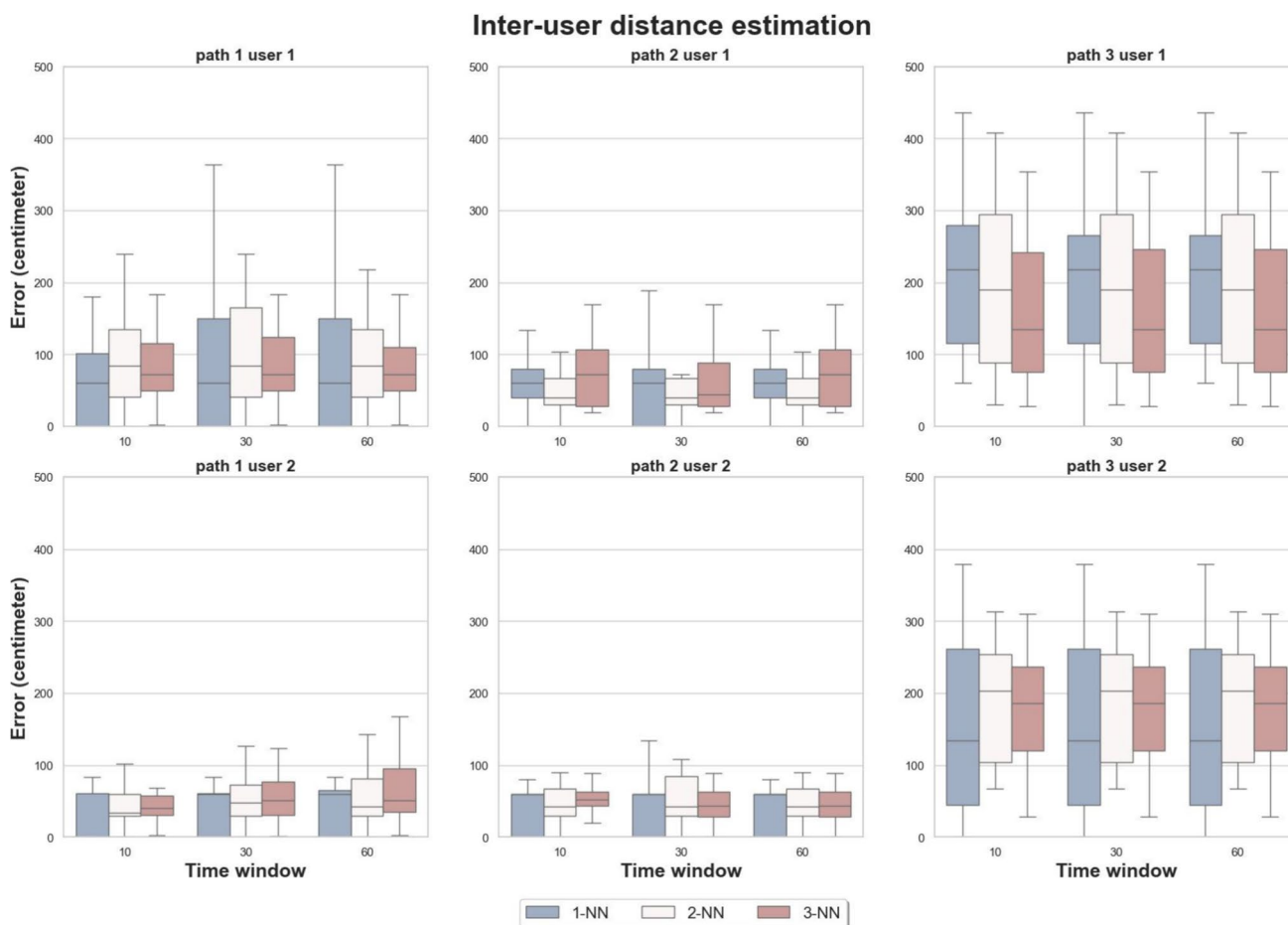


Fig. 10 Inter-User Distance Estimation Distributions

always occur in those related to the third path for both users, emphasizing the challenge of achieving an accurate estimate when the path bypasses the walkway where the sensors are installed. The best estimates are obtained with all-encompassing fingerprint maps for most test configurations, as shown in Fig. 11. The estimates for path 3 of User 1 yield the worst results for the above reasons.

In conclusion, we stress that for both intra- and inter-users, fingerprint maps built on tests with similar paths having a higher quantity of information return the lowest average error (e.g., path two evaluated with the fingerprint map built on path one in intra-user tests, independent of the considered user). This aspect emerges most clearly in inter-user tests performed with enhanced fingerprint maps, as shown in Fig. 12. The bars show that as the k-value increases, the average error decreases rapidly, especially for wider time windows in the most problematic cases (e.g., when estimates are performed for the third path of user 1 with the enhanced fingerprint map of user 2). These tests also show that 3-NN is the best trade-off as the time window increases. This is evident from the more balanced distributions and the dispersion of the values with respect to Q_1 and Q_3 . Finally, comparing the results of the inter-user estimation with the results obtained using the enhanced fingerprint maps, we note that the latter are better because of the more comprehensive information used to estimate the distance from the raw data.

For completeness, Fig. 13 shows a comparison of the cumulative distribution functions for intra-user, inter-user, and enhanced inter-user tests, evaluated over the entire results and under different k-NN settings. The x-axis represents the error, and the y-axis represents the cumulative probability, ranging from 0 to 1. A steeper curve indicates more concentrated lower error values, while a flatter curve indicates greater variability or higher errors.

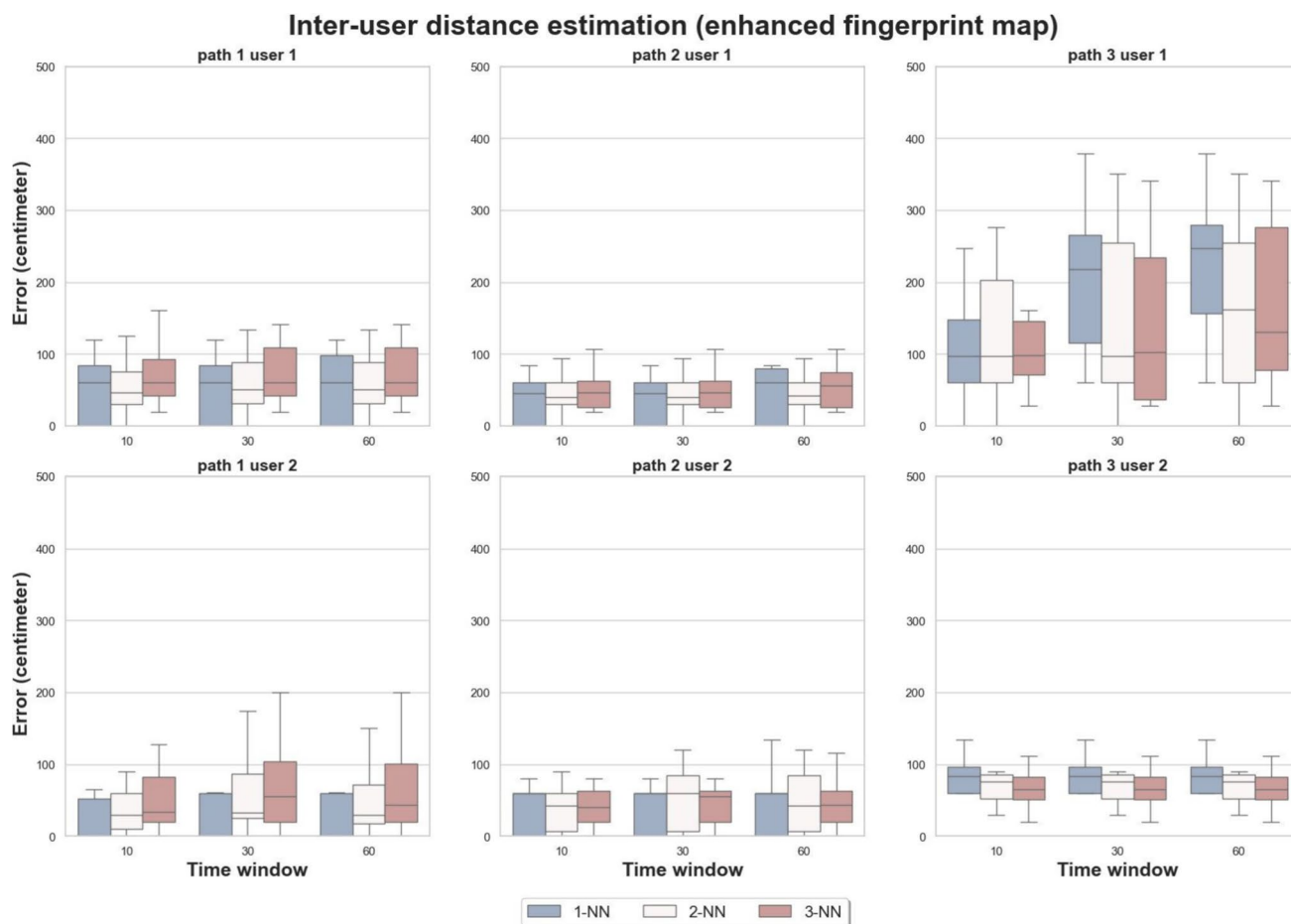


Fig. 11 Inter-user distance estimation distribution results using enhanced fingerprint maps

The inter-user enhanced fingerprint map (green curve) shows better performance with lower errors at higher cumulative probabilities, while the intra-user data (blue curve) shows higher errors across the range, indicating less favorable performance. The inter-user data (orange curve) performs in between. The analysis also shows that the error is less than 1 m in over 75% of cases in two out of the three test categories (upper plot), highlighting strong performance in these scenarios.

Ultimately, we observed that the performance of our system (i.e., errors under 1 m in over 75% of cases) aligns with the accuracy reported in existing indoor localization systems that utilize RF signals, as detailed in [3, 19]. These observations underscore that our approach, which uses underfloor accelerometers, provide competitive results compared to systems that use RF signals.

Furthermore, based on the results presented in [20], where the analyzed technologies demonstrate accuracies ranging from 0.12m to 2 m (with an average of 0.8m across all technologies), we can conclude that these values are fully consistent with the findings of our study.

5 Conclusion

In this study, we focus on the development and evaluation of a device-free indoor localization system that utilizes accelerometers for data collection and a fingerprinting technique for position estimation. Our motivation comes from the increasing demand for accurate indoor localization systems in various domains, including smart

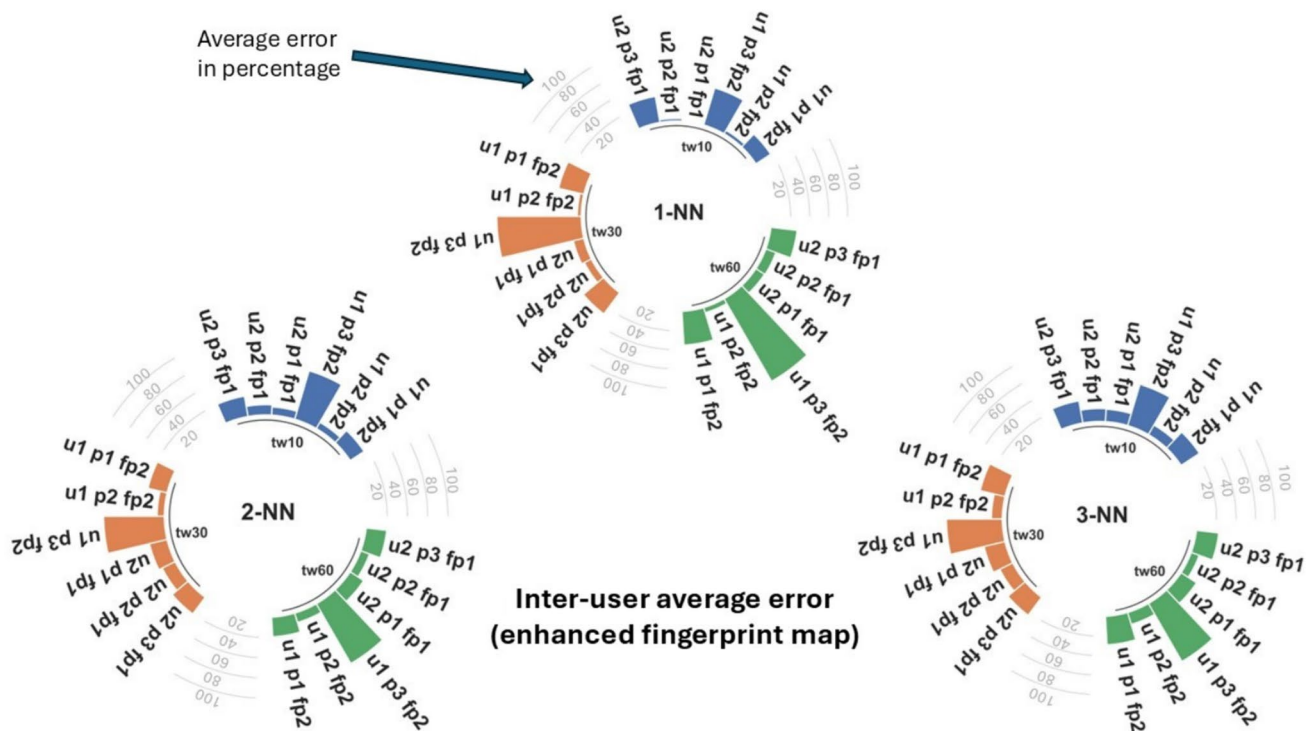


Fig. 12 Normalized average error for inter-user tests using enhanced fingerprint maps. Each circular bar plot represents the average error percentage for three types of tests, categorized based on the time window

buildings, healthcare, and retail, where the precise tracking of individuals within indoor spaces is crucial to providing context-sensitive services and enhancing operational efficiency.

Indoor localization systems have become indispensable tools in modern environments, offering precise tracking capabilities. In this context, we propose a device-free indoor localization system based on accelerometers for data collection and a fingerprinting technique to estimate the user’s position. These systems offer robust and reliable localization in diverse environments, while ensuring user privacy and comfort.

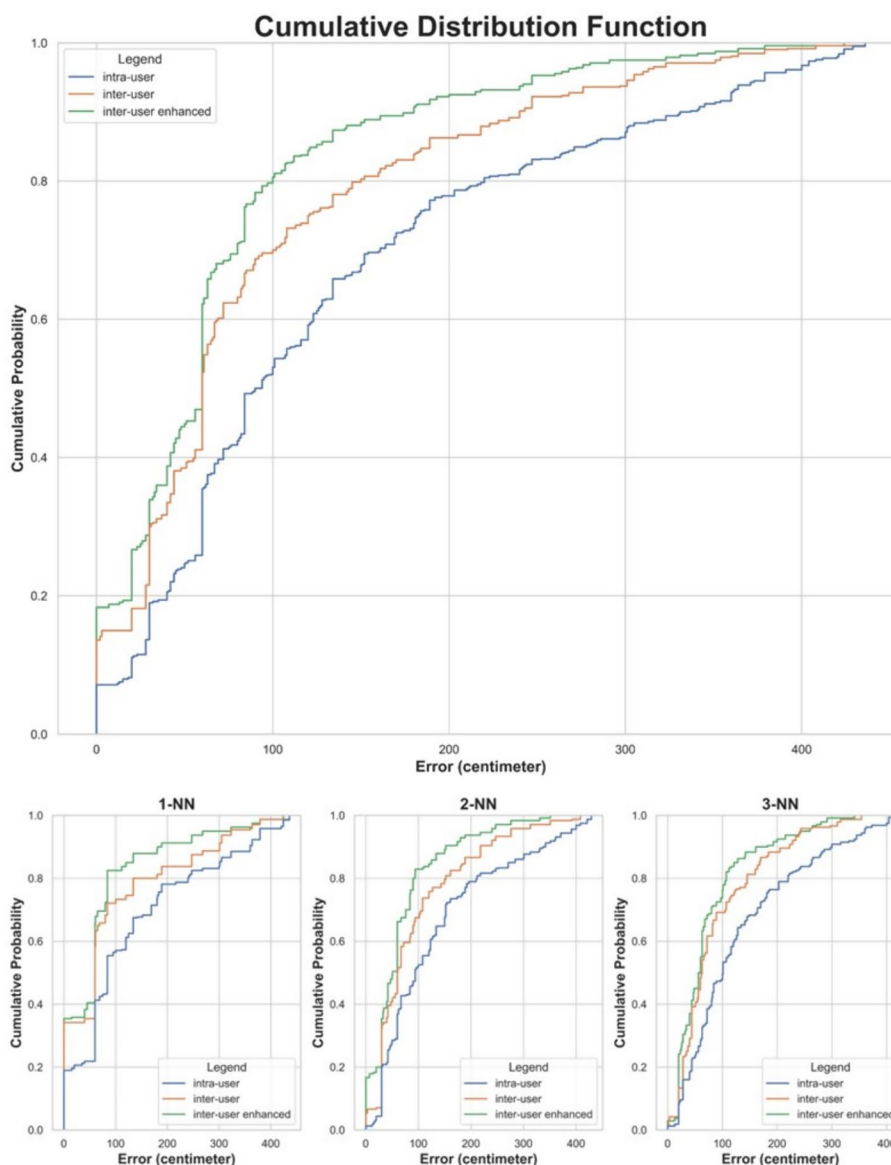
The proposed system offers advantages in dynamic environments, providing continuous motion tracking, robustness to environmental factors, and minimal calibration requirements, making them suitable for long-term deployment in various settings.

Our experimental results demonstrate the feasibility and effectiveness of our approach. Despite using a limited number of sensors and simple distance estimation strategies, such as k-nearest neighbors (k-NN), we achieved position estimates with an error comparable to pure fingerprinting techniques that exploit the strength of the receiver signal [16]. Furthermore, the results also show that good performance can be obtained without extensive effort in the data preprocessing phase. Such results identify it as a ready-to-use system, since it does not require a very long time between installation and deployment. In addition to the above results, we share the code used to obtain them, as well as the dataset generated with the proposed system during the experimental campaign.

The novelty of this study lies in the demonstration that the system works effectively in structures with floating floors. However, we recognize some limitations of the method proposed. For instance, the lack of system scalability. Each room requires its own dedicated setup, limiting its use in larger or more complex environments, although the system’s installation cost remains affordable due to the low-cost sensors employed.

Another limitation is the dependence of the system on the type of floor. The current implementation has been tested on a floating floor with removable self-locking tiles. The performance of the system on other types of flooring, such as concrete or fixed tiles, has not yet been investigated. Extending the applicability of the system to a wider range of floor types and exploring methods for scalability are promising directions for future work. Indeed,

Fig. 13 Cumulative distribution function illustrating the effectiveness for the performed tests



we investigated the sensing principle on a representative modular flooring system, which served as a controlled environment for assessing the fundamental viability of vibration-based localization. Since the method depends primarily on the mechanical coupling between the floor surface and subfloor structure, this configuration provides a realistic and widely applicable test case. Future work will explore additional flooring materials and constructions to examine how variations in mechanical properties influence vibration transmission and to determine the conditions under which the approach can be reliably extended to other indoor environments. Furthermore, in future advancements of our research, we plan to extend the collected dataset, perform extensive testing with additional indoor localization techniques, vary the number of sensor readings, and explore the range of application domains where our solution can be applied.

Author contributions Conceptualization: A.C., P.B.; Investigation: D.B., A.C., D.L.R., P.B.; Methodology: D.B., A.C., D.L.R., P.B.; Software: D.B., D.L.R.; Visualization: D.B.; Supervision: A.C., P.B.; Funding acquisition: P.B.; Writing - original draft & review: D.B., A.C., D.L.R., P.B.

Funding This work was funded by European Union - Next Generation EU, in the context of The National Recovery

and Resilience Plan, Investment Partenariato Esteso PE8 “Conseguenze e sfide dell’invecchiamento”, Project Age-IT, CUP: B83C22004880006

Data availability The dataset collected and the open source Python code used in this paper have been deposited on the Zenodo platform at the following link: <https://doi.org/10.5281/zenodo.10838489>

Code availability A link to a replication package that contains the data and the analysis code is also available in Zenodo repository, <https://doi.org/10.5281/zenodo.10838489>

Declarations

Conflict of interest The authors have no financial or proprietary interests in any material discussed in this article.

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Publisher’s Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

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