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Communication

Towards Ambient Intelligence-based Environments for Fall Detection and Indoor Localization: Methodology for a Simplistic Design for Real-World Implementation

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Abstract: Falls, highly common in the constantly increasing global aging population, can have a variety of negative effects on their health, well-being, and quality of life, including restricting their capabilities to conduct Activities of Daily Living (ADLs), which are crucial for one's sustenance. Timely assistance during falls is highly necessary, which involves tracking the indoor location of the elderly during their diverse navigational patterns associated with ADLs, to detect the precise location of a fall. With the decreasing caregiver population on a global scale, it is important that the future of intelligent living environments can detect falls during ADLs while being able to track the indoor location of the elderly in the real-world. Prior works in these fields have several limitations, such as – lack of real-world testing, lack of functionalities to detect both falls and indoor locations, high cost of implementation, complicated design, the requirement of multiple hardware components for deployment, and the necessity to develop new hardware or software for implementation, which make the wide-scale deployment of such technologies challenging. To address these challenges, this work proposes a simplistic design paradigm for the development of an ambient intelligence-based living environment with functionalities to perform indoor localization and fall detection during ADLs. The hardware necessary for the development of this system involves integration of easily available sensors, the combined cost of which is USD 262.15 – which upholds its cost-effectiveness. The results from real-world experiments that were performed uphold the effectiveness of the system design to capture multimodal components of the user interaction data during ADLs that are necessary for the detection of falls as well as indoor localization.

Keywords: elderly; aging population; ambient intelligence; fall detection; indoor localization; real-world implementation; sensors; activities of daily living; assisted living

1. Introduction

Growing worldwide longevity is now more commonplace than ever before, with the average life expectancy reaching 60 years or higher. This is mostly due to medical breakthroughs and advances in healthcare research [1]. The population of the world over the age of 65 is increasing dramatically, numbering 962 million today, and projected to increase to 2 billion by 2050 [2,3]. As the population ages, modern society is facing a wide range of difficulties stemming from numerous conditions associated with the elderly, such as varying rates of decline in behavioral, social, emotional, mental, psychological, and motor abilities, as well as other issues such as cognitive impairment, behavioral disorders, disabilities, neurological disorders, Dementia, Alzheimer's, and visual impairments, that are associated with the process of aging.

Over the last few years, the aging populations throughout the globe have had to contend with a decrease of caregivers to care for them, which has created a variety of challenges and difficulties [5-7]. Here, two of the key challenges will be discussed. First, as the

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demand has increased, the cost of caregiving has risen considerably in recent years. As a result, affording caregivers is becoming increasingly difficult. Second, quite often, caregivers take care of multiple elderly people with multiple varying needs during a day; as a result, they are frequently exhausted, overworked, overwhelmed, and overburdened, which affects the quality of care.

Research predicts that the worldwide population comprising of both the elderly and the young will live in smart homes, smart communities, and smart cities in the coming years. Research by [8] estimates that 66 percent of the world's population will live in smart homes by 2050. Thus, due to the scarcity of caregivers and the expected emergence of smart homes on a global scale [9], the future of technology-driven Internet of Things (IoT)-based living spaces, such as smart homes, must be able to contribute to Ambient Assisted Living (AAL) for the elderly by detecting, interpreting, analyzing, and anticipating different needs within the context of their ADLs.

AAL may broadly be defined as the use of networked, automated, and/or semi-automated technological solutions within people's living and working surroundings to improve their health and well-being, quality of life, user experience, and independence [10]. In general, ADLs may be considered as the everyday activities needed for one's sustenance done in one's living surroundings [11]. Categories of ADLs include personal hygiene, dressing, eating, continence management, and mobility.

As one becomes older, one becomes more prone to falling. As per [12], a fall is defined as a sudden drop onto the ground or floor resulting from being pushed or pulled, environmental factors, fainting, or any other analogous health-related issues, difficulties, or impairments. Falls can have many consequences on the health, well-being, and quality of life of the elderly, such as making it difficult for them to complete ADLs. On a worldwide scale, falls are the second most common cause of unintentional fatalities. Older individuals are at an increased risk of suffering a traumatic brain injury due to falling [13]. On an annual basis, around one in every three older persons fall at least once a year, and it is estimated that the percentage of those who fall will rise by around 50% soon [14,15]. Falls have been a major concern for the worldwide elderly population. In the United States alone, 30% more people have died from falls since 2009. Every 11 seconds, an elderly person who has fallen and is injured must be sent to the hospital for urgent care. An older adult in the United States dies every 19 minutes from a fall. Every year, there are approximately 3 million emergency room visits, 800,000 hospitalizations, and more than 32,000 fatalities among the elderly due to falls [16–18]. The rate of injuries and fatalities from falls is rising consistently. By 2030, in the United States, research predicts that there will be seven deaths per hour from falls. The yearly cost of medical and healthcare-related costs connected to falls among the elderly is USD 50 billion. This figure is expected to grow not only in the U.S. but also on a global scale [19]. A fall can have various reasons, which can be roughly classified as internal and external [20]. External causes are related to the environmental variables in the spatial confines of the individual that might contribute to a fall. These include slippery surfaces, staircases, and so forth. Individual variables such as impaired eyesight, cramping, weakening in muscular skeleton structure, chronic diseases, and so on are examples of internal reasons for a fall. In addition to the consequences of mild to serious physical injuries, falls can have a wide range of effects on different areas of well-being, including personal, social, emotional, and cognitive well-being. Individual—injuries, bruising, blood clots; social life—reduced mobility leading to loneliness and social isolation; cognitive or mental—fear of moving about, lack of confidence in doing ADLs; and financial—the expense of medical treatment and caretakers.

It is just as important to figure out whether a long period of lying down occurs after a fall. After falling on the ground for almost an hour, a person who cannot get up on their own suffers from a long lie [20]. The work in [21] reports that 47% of persons who experience a fall also experience a long lie. Additionally, about half of the elderly who experience a long lie will likely die in the next six months [22]. Elderly people are more likely to suffer a myriad of health-related issues due to lying on the ground for lengthy periods, including localized muscle soreness, tissue injury, pressure sores, nerve issues, carpet burns,

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dehydration, hypothermia, pneumonia, and fear of falling [20]. Thus, it is important that the future AAL systems in the living environments of the elderly can track falls and detect long lies.

To accurately detect falls and the other dynamic and diversified needs of the elderly that usually arise in the context of their living environments during ADLs, tracking and analysis of the indoor spatial and contextual data associated with these activities are highly crucial. Technologies such as Global Positioning Systems (GPS) and Global Navigation Satellite Systems (GNSS) have transformed navigation research by allowing people, objects, and assets to be tracked in real-time. Despite their great success in outdoor contexts, these technologies are still unsuccessful in indoor settings [23]. This is due to two factors: first, these technologies rely on line-of-sight communication between GPS satellites and receivers, which is not achievable in an interior setting, and second, GPS has a maximum accuracy of up to five meters [24]. An Indoor Localization System is a network of systems, devices, and services that assist in tracking and locating persons, objects, and assets in indoor environments where satellite navigation systems like GPS and GNSS are ineffective [25]. Thus, Indoor Localization becomes highly relevant for AAL so that the future of technology-based living environments such as Smart Homes can take a comprehensive approach towards addressing the multimodal and diverse needs of the elderly during different ADLs as and when such needs arise. Despite recent advances in AAL research, when considering the development of smart home technologies, numerous challenges remain, as mentioned in detail in Section 2. These challenges are primarily centered around - lack of real-world testing, lack of functionalities in the frameworks to detect both falls and indoor locations, high cost of implementation, complicated design paradigms, the requirement of multiple hardware components for deployment, and the necessity to develop new hardware or software for implementation, which make the wide-scale deployment of such technologies challenging. To address these challenges, it is crucial to develop a simplistic design and methodology for the development and deployment of AAL systems that can perform both fall detection and indoor localization in the future of intelligent living environments, such as Smart Homes. Addressing this challenge serves as the main motivation for the work proposed in this paper. This paper is presented as follows. Section 2 reviews the recent works in this field and elaborates on the challenges and limitations that exist in these systems. Section 3 presents the methodology and concept for the development of the proposed system. Section 4 presents the results and discussions. It is followed by Section 5, which concludes the paper and outlines the scope for future work in this field.

2. Literature Review

In this section, a comprehensive review of recent works in Indoor Localization and Fall Detection that focused on Ambient Assisted Living is presented.

Varma et al. [26] developed an indoor localization system using a Random Forest-driven machine learning approach based on data gathered from 13 beacons installed in a simulated IoT infrastructure. To get the user's location, the researchers processed the data from all these beacons. The development of a neural network-based indoor WiFi fingerprinting method by Qin et al. [27] enabled a user's position to be pinpointed in an indoor setting. They examined their findings on two datasets to discuss the effectiveness of their work. The user's position was detected using a decision tree-based technique in the research proposed by Musa et al. [28]. The system design included a non-line-of-sight approach, multipath propagation tracking, and ultra-wideband technique. Similarly, a decision tree-based method for indoor location detection was presented by Yim et al. [29]. The system was able to use WiFi fingerprinting data to build the decision tree offline. According to Hu et al. [30] 's technique, a k-NN classification methodology with contextual data from an indoor environment can locate a person's indoor position by using the access point the person was closest to after accessing it. Poulose et al. [31] developed a deep learning-based method for indoor position recognition that employed Received Signal Strength Indicator (RSSI) signal data to train the learning model. Barsocchi et al. [32]

utilized a linear regression-based learning technique to build an indoor positioning system that used RSSI values to track the user's distance from reference locations and subsequently translated the same numerical value to a distance measure to locate the user's real position. Kothari et al. [33] created a cost-effective, user-location-detecting smartphone application. 4 volunteers were included in the trials to evaluate the technique, which merged dead reckoning with WiFi fingerprinting. Wu et al. [34] created an indoor positioning system using data from new sensors incorporated into the users' mobile phones that could utilize user motion and user behavioral features to create a radio map with a floor plan, which could subsequently be used to determine the users' indoor positions. The researchers recruited a total of 4 participants to evaluate their framework. Gu et al. [35] suggested a step counting method that could address challenges such as overcounting of steps and false walking while tracking the user's indoor location; that was validated by taking into consideration the data collected from 8 participants.

Following the above, we examine recent AAL advances related to fall detection. An algorithm designed by Rafferty et al. [36] used thermal vision to track falls during ADLs. The system architecture involved installing thermal vision sensors on the ceiling in the confines of the user's living space, and then computer vision algorithms were used to identify falls. In the work of Ozcan et al. [37], the camera had to be carried by the user instead of being installed at various locations. A decision tree-based technique was utilized to identify falls based on images taken by the user's camera about multimodal components of the data gathered from the image sensors. A wearable device for fall detection was developed by Khan et al. [38]. This gadget had a three-part assembly: a camera, a gyroscope, and an accelerometer, all of which were connected to a computer that comprised the system architecture to detect falls. The work of Cahoolessur et al. in [39] introduced a binary classifier-based device capable of finding anomalies in behavioral patterns such as falls in a simulated IoT-based environment. To design the wearable gadget, the authors first developed a model for the user, using a cloud computing-based architecture, which was followed by implementation and testing of the same.

As can be seen from these recent works [26-39] in the field of AAL, the following challenges exist in these systems:

1. The AAL-based fall detection systems cannot currently track the user's indoor location. It is highly essential that, in addition to being able to track, analyze, and interpret human behavior, such systems are also able to detect the associated indoor location so that the same can be communicated to caregivers or emergency responders to facilitate timely care in the event of a fall or any similar health-related emergencies. Delay in care from a health-related emergency, such as a fall, can have both short-term and long-term health-related impacts. Similarly, the AAL-based indoor localization systems cannot detect falls during ADLs.
2. These methodologies use multiple sensors and hardware systems that need to be installed in the living confines of the user. Some examples include - 13 beacons [26], WiFi access points and WiFi fingerprint capturing architecture [29,30], RSSI data capturing methodologies [31,32], thermal vision sensors [36], and cameras [37] that need to be carried by the users. Installing such sensors across smart communities or smart cities that could represent multiple interconnected smart homes would be highly costly. To add, as elderly are usually receptive to the introduction of multiple new technologies [40], they might reject the adoption or process of familiarization when multiple such sensors are installed in their day-to-day living environments.
3. The design process for the development of some of these systems [26,29-32,36,37] is complicated as it involves the integration and communication of multiple software and hardware components.
4. Some of the works have also involved the development of new applications – such as the smartphone-based application proposed in [33] and the wearable gadget proposed in [39]. Replicating the design of a mobile application has several challenges unless it is replicated or re-developed by the original developers

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[41]. In the context of wearables, it is crucial to ensure that the design methodology follows the 'wearables for all' design approaches [42] as well as the paradigms of universal design, which are not discussed in detail in [39].

5. Some of these approaches have been tested on datasets - such as [27], which were collected in specific environments, so it is difficult to comment if the approaches would achieve the same accuracy in real-world settings.

To address the above limitations, we propose a simplistic design for an AAL framework for fall detection and indoor localization during ADLs in real-world settings. The system architecture is discussed in the next section.

3. Methodology and System Design

This section outlines the design process for the development of the proposed ambient intelligence-based system for fall detection [44] and indoor localization [45]. The system archiecture involves integration of the data available from a set of easily available and cost-effective sensors, the specifications of which are outlined in the latter part of this section. This functionliaity of the system is based on the findings of two of our prior works in this field which proved that accelerometer and gyroscope data collected from wearables could be utilized to develop fall detection and indoor localization systems. These frameworks were tested on datasets as outlined in these respective papers [44,45]. In this paper, we extend both these works by (1) proposing a simplistic design and methodology for real-world development of these functionalities in a combined manner; (2) developing a software solution based on this simplistic design and discussing the effectiveness of the same in terms of data collection, seamless intergration of the sensors, and successful communication between the software and the sensors; and (3) discussion of preliminary results based on real-world deployment of the proposed system that upholds its efficacy and performance. These respective functionalities for fall detection and indoor localization are outlined in 3.1 and 3.2, respectively. The proposed design and the associated system specifications that integrate both these functionalities [44,45] as a software solution for a real-world environment are presented in Section 3.3.

3.1. Methodology for Fall Detection during ADLs

This approach's design specification [44] comprises four main components: pose detection, data collecting and preprocessing, learning module, and performance module. To identify the user's position at any given time, the pose detection system utilizes motion and movement-related data during ADLs to deduce the user's instanteneous position. The study of accelerometer data during various activities at various timestamps is one way of creating such a pose identification system. This is measured by computing the acceleration vector and the acceleration's orientation angles measured on all three axes.

In the past, these inertial sensors worked by suspending a proof mass, m, from a mechanical framework using a spring, km, which then responded to a force, F, which indicated the value the sensor is supposed to measure. The instrument used to sense the related force would cause a shift, x, in the present proof mass due to the force applied. For example, if the device is an accelerometer, the input force will be caused by the acceleration of the mass. If the instrument were a gyroscope, the Coriolis acceleration induced by the angular rotation of the proof mass would create the input force. This system makes use of sophisticated inertial sensors, which include three-axis accelerometers. Consequently, the results of such sensors rely on the device's motion and the person using it [46,47]. It is possible to calculate a three-axis accelerometer sensor's velocity and orientation angle by utilizing the acceleration values it measures in three directions: X, Y, and Z. The relative vector projections of a three-dimensional acceleration vector, expressed in the sensor's coordinate system, are also produced by such advanced sensors. The accelerometers are typically attached to various parts of the person's body depending on the body part(s) from which acceleration data needs to be computed. To calculate the sensor orientation angle and differentiate different poses, these sensors use the "g" value (acceleration due to gravity). The orientation angle here implies the angle formed by the acceleration vector with the three axes in a coordinate system.

Every posture, motion, and movement may be investigated by computing these orientation angles as a unique spatial orientation during different stages or steps of any given ADL. In this case, the location of the sensor on the body is equally essential. An accelerometer positioned on the chest of a person, for instance, is always at 90 degrees with the floor for motions like standing and sitting but at 0 degrees with the floor for other types of movements like lying on the ground or being in a stance in which both arms and legs are touching the floor. In analyzing postures or poses related to various ADLs, the purpose is to compute orientation angles along the three axes. If the user is moving, they will adopt dynamic postures. The rapid changes in the values of the acceleration angles can be used to identify falls or motions associated with falls during all such postures. The approach for collecting and preparing data is part of the data collection and preprocessing module of this system. It is important to remove data attributes that aren't needed to create a machine learning classifier before going on to the next step, which is filtering useful information from the remaining data. This approach was tested on two datasets [44], and in this paper, we extend the same towards its real-world implementation in additon to including the methodology for indoor localization while proposing a simplistic design for the associated software development that is cost-effective in nature.

3.2. Methodology for Indoor Localization during ADLs

The development of the proposed approach [45] for acceleration and gyroscope data-based indoor localization during ADLs involves the following steps:

1. The associated representation scheme involves mapping the entire spatial location into non-overlapping 'activity-based zones' [45], distinct to different complex activities, by performing complex activity analysis [48].
2. Analyze the ADLs in terms of the atomic activities, context attributes, core atomic activities, core context attributes and their associated threshold values based on probabilistic reasoning principles [48].
3. Infer the semantic relationships between the changing dynamics of these actions and the context-based parameters of these actions.
4. Study and analyze the semantic relationships between the accelerometer data, gyroscope data, and the associated actions and the context-based parameters of these actions within each 'activity-based zone'.
5. Study and analyze the semantic relationships between the accelerometer data, gyroscope data, and the associated actions and the context-based parameters of these actions across different 'activity-based zones' based on the sequence in which the different ADLs took place and the related temporal information.
6. Integrate the findings from Step 4 and Step 5 to interpret the interrelated and semantic relationships between the accelerometer data and the gyroscope data with the location information associated with different ADLs that were successfully completed in all the 'activity-based zones' in the given indoor environment.
7. Split the data into the training set and test set and develop a machine learning-based model to detect the location of a user in terms of these spatial 'zones' based on the associated accelerometer data and gyroscope data.
8. Compute the accuracy of the system by using a confusion matrix.

The methodology was tested on a dataset [45] that supported its relevance and effectiveness. In this paper, we extend the same towards its real-world implementation in additon to including the methodology for fall detection while proposing a simplistic design for the associated software development that is cost-effective in nature.

3.3. Methodology for Indoor Localization and Fall Detection: Real-World Implementation

The development of the proposed system, including its design and specifications by incorporating the functionalities for fall detection [44] and indoor localization [45], is presented in this section. The design process involves the integration and development of the system architectures for both these functionalities (outlined in Sections 3.1 and 3.2, respectively) in the form of software solution, that funtioned by communicating and interfacing with different sensors in a simulated IoT-based environment. The design process was centered around the development of a data collection software that would help to develop a dataset consisting of multimodal features of user interaction data during ADLs that are necessary for fall detection systems and indoor localization systems to function in a seamless manner. This system was developed, implemented, and deployed at the Ambient Assisted Living Research Lab located at 411 Science Building, University of Cincinnati Victory Parkway Campus.

The developed framework leveraged several methods from multiple disciplines to extract the interdependent and multi-level semantic relationships between user interactions, context parameters, and daily activities concerning the dynamic spatial, temporal, and global orientations of the user towards the creation of the proposed dataset that would facilitate the analysis of human activities, behavioral patterns, and their fine-grain components in a real-world scenarios and help to detect falls in specific indoor locations. The implementation of this proposed work involved the use of multiple sensors. The spatial mapping involved the use of smart cameras. TrendNet TV-IP324PI Dome Style Cameras [49] or the Imou Bullet 2S cameras [50] could be used for this purpose. Based on the findings of the works described in Sections 3.1 and 3.2, six TrendNet TV-IP324PI Dome Style Cameras were used for the development of the software framework. Alternatively, the working of the Imou Bullet 2S cameras was evaluated, and it was observed that only two such cameras are sufficient for mapping the entire indoor space in the research lab where this data collection system was set up. The Imou Bullet 2S is a smart camera that can directly connect to WiFi and has features such as infrared mode, color mode, smart mode, and human detection. The Sleeve Sensor Research Kit from Mbient Labs [51] comprised the wearable component of this design, which has several components to record the different characteristics of motion and behavior data. These include an Accelerometer, Gyroscope, Magnetometer, Sensor Fusion, Pressure Sensor, and Temperature Sensor. Specificallym this MMS sensing system consists of a wearable device with the following sensors: 6-axis Accelerometer + Gyroscope, BMI270 Temperature, BMP280 LTR-329ALS, BMP280 Barometer/Pressure/Altimeter, Ambient Light/Luminosity Magnetometer, with three axes, BMM150 Sensor Fusion, 9-axis BOSCH 512MB memory, Lithium-ion rechargeable battery, Bluetooth Low Energy, CPU, button, LED, and GPIOs. The data collected from this sensor allowed us to capture various dynamics of user interactions and user behavior during different ADLs performed by the participants in the experimental setup.

The Estimote Proximity Beacons [52] were used to track the proximity of the user to different context parameters as well as to detect the presence or absence of the user in a specific 'activity-based zone' [45]. Each beacon has a low-power ARM® CPU, e.g., 32-bit, 64 MHz CPU, a quad-core, 64-bit, 1.2 GHz CPU in Mirror flash memory to store apps and data, 8 G.B. in Mirror RAM memory for the apps to use while running, 1 G.B. in Mirror, a Bluetooth antenna and chip to communicate with other devices, and between the beacons themselves. Figure 1 shows the screenshot from the user interface of the software, which shows the real-time data collection from the Sleeve Sensor Research Kit from Mbient Labs during one of the experiments.

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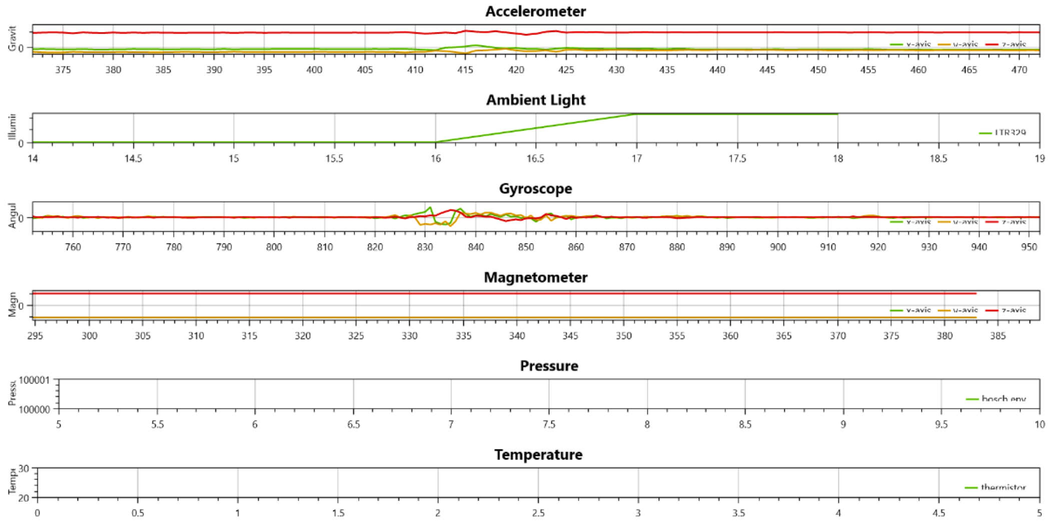

Figure 1. Real-time data collection from the Sleeve Sensor Research Kit from Mbient Labs during one of the experiments

Figure 2 is a screenshot taken from the software used to capture the real-time video feed from the TrendNet TV-IP324PI Dome Style Cameras. The screenshot shows the details and specifications of 4 cameras recording the data for one of the specific experimental trials, and Figure 3 shows one of these cameras in operation where it was pointing towards a wall at a specific time instant.

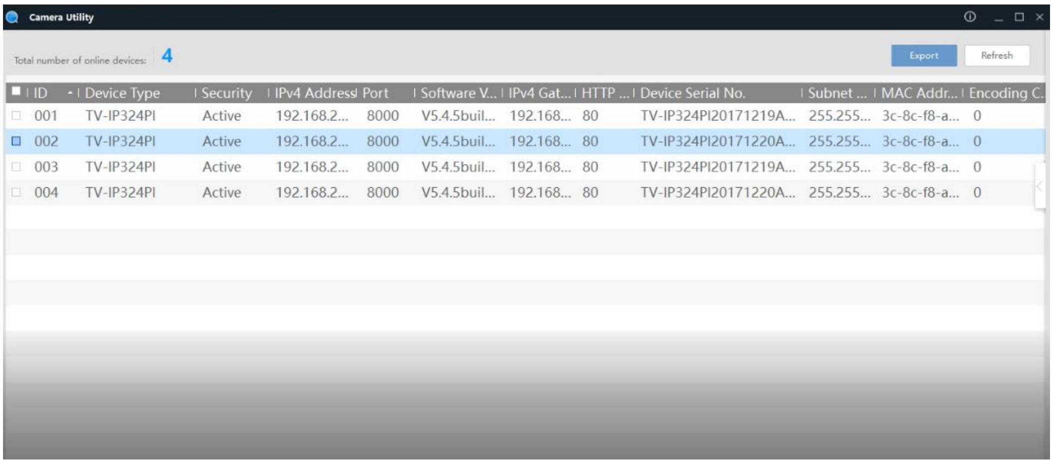

Figure 2. Details and specifications of 4 cameras recording the data for one of the specific experimental trials

Figure 4 shows the Sleeve Sensor Research Kit. This image is provided separately as due to the small size of the sensor, it is difficult to track the location of the sensor in the images from the experiments, which are provided in Section 4. During the experiments, as per the methodology described in Sections 3.1 and 3.2, this sensor was mounted on the user's chest to collect the data during different ADLs performed in different 'activity-based zones'. Figures 5 and 6 show the placement of multiple proximity sensors in different 'activity-based zones'. Figures 7 and 8 show the strategic and calculated placement of the two Imou smart cameras, which helped to map the entire available space in the research lab.

Microsoft SQL Server version 11.0 [53] was used to develop the database which is an integral part of the proposed software solution. The solution was developed to communicate and interface with all these sensors to capture and integrate the data in the form of different attributes in the database. Microsoft SQL Server is a Relational Database

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Management System (RDBMS) developed by Microsoft. These sensors were specifically chosen for the following reasons:

1. These sensors can be programmed to capture the specific behavioral data that is necessary to detect both falls and indoor locations.
2. They are easily available and cost-effective.
3. Integration of these sensors towards the development of a software solution that can communicate with all these sensors is not complicated.
4. The design process both for the experiments and for the system architecture becomes convenient due to the specifications, coverage, and characteristics of these sensors.

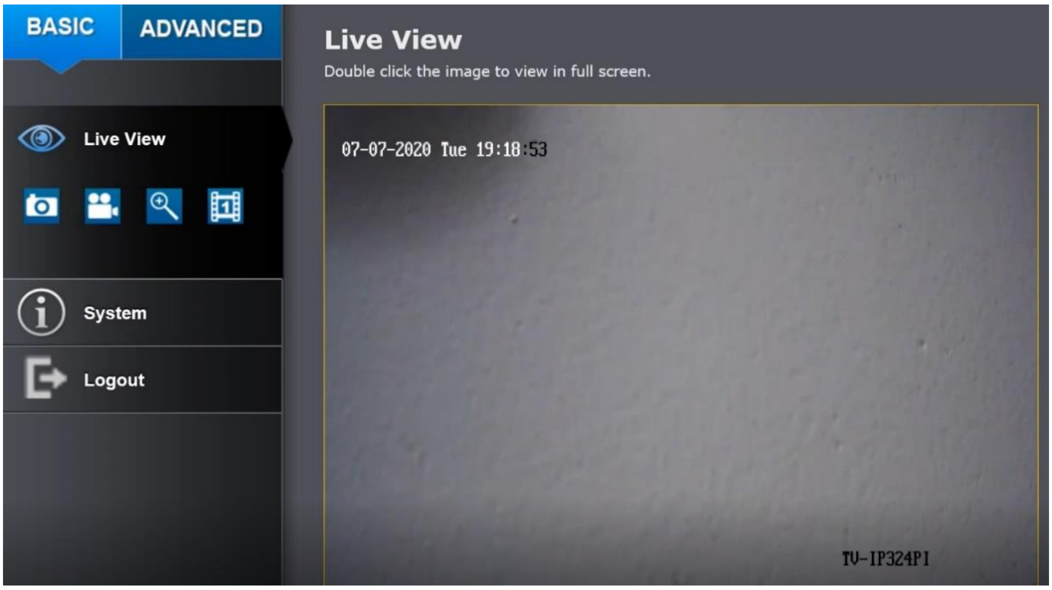

Figure 3. Live view from one of the TrendNet TV-IP324PI Dome Style Cameras in action when it was pointed towards a wall at a specific time instant.

Figure 4. The Sleeve Sensor Research Kit

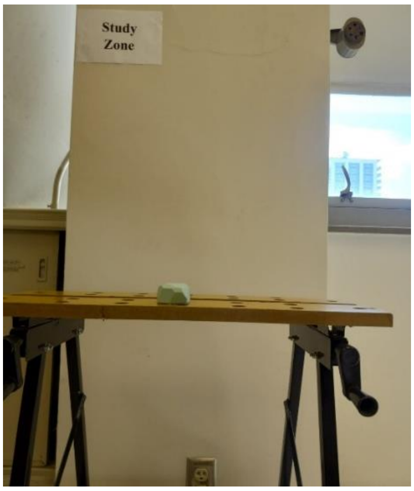

Figure 5. Placement of one of the proximity sensors in the 'Study-Zone.'

Figure 6. Placement of all the proximity sensors in the 'Study-Zone.'

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Figure 7. Placement of one of the Imou Smart Cameras

Figure 8. Placement of the second Imou Smart Camera

As can be seen from Figures 7 and 8, dedicated strategic locations (marked as Camera 1 zone and Camera 2 zone) were assigned in the lab space for the setting up of both these Imou Smart cameras. The cost of these sensors (at the time of purchase) is outlined in Table 1. As outlined in this section, either two Imou Smart Cameras or six Trendnet cameras can be used for the proposed system design. One Mbient Labs MMS Sensor is sufficient as long as there is only one user in the given IoT-based environment. Four proximity sensors were used for the experimental setup designed in the simulated IoT-based space to represent the different zones and their associated context parameters. Therefore, from Table 1, the minimum cost for implementation of this system design to develop both fall detection and indoor localization functionalities would be: Cost of two Imou Smart Cameras (2*$29.58) + Cost of one Mbient Labs MMS Sensor (1*$103.99) + Cost of four Proximity Sensors (4*$24.75)=$262.15. This upholds the cost-effectiveness of the proposed system. Alternatively, if the system designer prefers to use the TrendNet TV-IP324PI Dome Style Cameras instead of the Imou Smart Cameras, the cost would be the Cost of six TrendNet TV-IP324PI Dome Style Cameras (6*$97.76) + Cost of one Mbient Labs MMS Sensor (1*$103.99) + Cost of four Proximity Sensors (4*$24.75)=$789.55. Here, two alternatives in terms of the TrendNet TV-IP324PI Dome Style Cameras and Imou Smart Cameras have been discussed. Based on our results from setting up the systems using both these alternatives, we did not observe any differences or challenges in either approach for capturing the user behavior data during ADLs. Furthermore, the Imou Smart Cameras also have the capability for human detection, which is not present in the TrendNet TV-IP324PI Dome Style Cameras. In view of this additional functionality, lesser cost, and the fact that a lesser number of Imou Smart Cameras are required for the system design, we propose the utilization of the same for the development of such systems.

Table 1. Costs of the sensors that are necessary for development of the proposed system.

Sensor	Cost per unit in USD
Imou Smart Camera	$29.99
TrendNet TV-IP324PI Dome Style Cameras	$97.76
Mbient Labs Sleeve Sensor	$103.99
Proximity Sensors	$24.75

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4. Results and Discussions

This section outlines the implementation details and preliminary results of the proposed system design to develop the AAL-based environment for fall detection and indoor localization. This work was performed by taking into consideration the safety and protection of human subjects (listed as participants in some images). Therefore, the CITI Training provided by the University of Cincinnati that comprises the CITI Training Curriculum of the Greater Cincinnati Academic and Regional Health Centers [54] was completed. Thereafter, approval for this study was obtained from the University of Cincinnati's Institutional Review Board (IRB) [55] with IRB Registration #: 00000180, FWA #: 000003152, and the IRB ID for this study was 2019-1026. Figure 9 shows the spatial mapping of two 'activity-based zones' in the simulated IoT-based environment. Figures 10-20 show the images captured from the recordings from the Imou smart cameras during one of the participants performing different ADLs in these 'activity-based zones'. The experiment protocol included the participant navigating across different 'activity-based zones' and performing different ADLs. The performance of the ADLs included different behaviors such as walking, stopping, falling, lying down, getting up from lying, etc., as represented in these figures. These activities were tracked by the Imou smart cameras, Mbient Labs Sleeve Sensor, and the Proximity Sensors. The Mbient Labs Sleeve Sensor was mounted on the participant's chest during the entire duration of the experimental trials. The Imou smart cameras were placed at two strategic and calculated locations that helped to track all ADLs performed in all the simulated 'activity-based zones'. The proximity sensors helped to detect the participant's presence or absence in each of these 'activity-based zones' in the context of different behavioral patterns. The software that communicated with all these sensors in real-time was developed on a Microsoft Windows 10 computer with an Intel (R) Core (T.M.) i7-7600U CPU @ 2.80 GHz, two core(s), and four logical processor(s). This software communicated with all these sensors to capture the associated data and develop a database with the different data represented as different attributes in the database.

Figure 9. Overview of the lab space showing two 'activity-based zones' (bedroom zone and study zone) with multiple contextual parameters

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Figure 10. A participant sitting on a couch in the relaxation zone

Figure 11. A participant standing near a couch in the relaxation zone

Figure 12. A participant walking from the relaxation zone to the bedroom zone

Figure 13. A participant sitting in the bedroom zone

Figure 14. A participant lying in the bedroom zone

Figure 15. A participant getting up from lying (stage 1) in the bedroom zone

Figure 16. A participant getting up from lying (stage 2) in the bedroom zone

Figure 17. A participant falling (stage 1) in the relaxation zone

Figure 18. A participant falling (stage 2) in the relaxation zone

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Figure 19. A participant falling (stage 3) in the relaxation zone. Here, a forward fall is demonstrated.

Figure 20. A participant falling (stage 3) in the relaxation zone. Here, a sideways fall is demonstrated.

Figures 10-20 are a representation of some of the behavioral patterns that the human subjects exhibited during these experimental trials in the different 'activity-based zones'. For each of these behavioral patterns, the associated acceleration data and gyroscope data in X, Y, and Z directions were captured by the Mbient Labs Sleeve Sensor. The indoor location of the participant was deduced based on the data obtained from the proximity sensors as well as the Imou Smart Cameras. During the experiments, certain behaviors such as a fall were observed to take place in small steps or stages. To accurately track each of these steps and if one step led to the other, we marked the same as stage 1, stage 2, etc., during the data collection process, which is further represented in some of these Figures. Furthermore, we also explored different ways by which each of these behaviors could be performed, for instance exploring the different ways of falling – forward fall and a sideways fall, as shown in Figures 19 and 20, respectively.

The original plan was to test all the proposed functionalities of this system design by including about 20 volunteers (ten males and ten females) for user diversity [56]. But no one predicted the widespread of the COVID-19 pandemic [57], the declaration of a national emergency in the United States on account of the same [58], and the subsequent lockdown for several months with more than 208,263,872 cases of COVID-19 with 4,379,612 deaths on a global scale. In the United States alone, at the time of writing this paper, there have been 37,469,989 cases of COVID-19 with 637,572 deaths [59]. Therefore, it was not possible to recruit 20 volunteers. As a result, a lesser number of volunteers participated in the data collection/database development process. This is one of the limitations of this study, which we plan to address in the near future by recruiting more volunteers for the experiments. All the experimental trials were conducted as per the guidelines for reducing the spread of COVID-19, recommended by both the Centers for Disease Control [60] and the University of Cincinnati [61]. These guidelines also involved following the University of Cincinnati's recommendations (at the time of conducting these experiments) to wear a mask in indoor environments, including classrooms and research labs, so the participant shown in Figures 10-20 can be seen wearing a mask.

The Big Data collected from multiple sensors during the experimental trials of all the participants was integrated to develop a dataset on MS SQL Server with different attributes representing the different data that was collected from different kinds of motions and behavioral patterns during the different ADLs performed in each of these zones. The dataset was developed on a Microsoft Windows 10 computer using the Windows Authentication feature of the SQL Server. Figures 21 and 22 represent the interface of the MS SQL Server and the database table that was developed.

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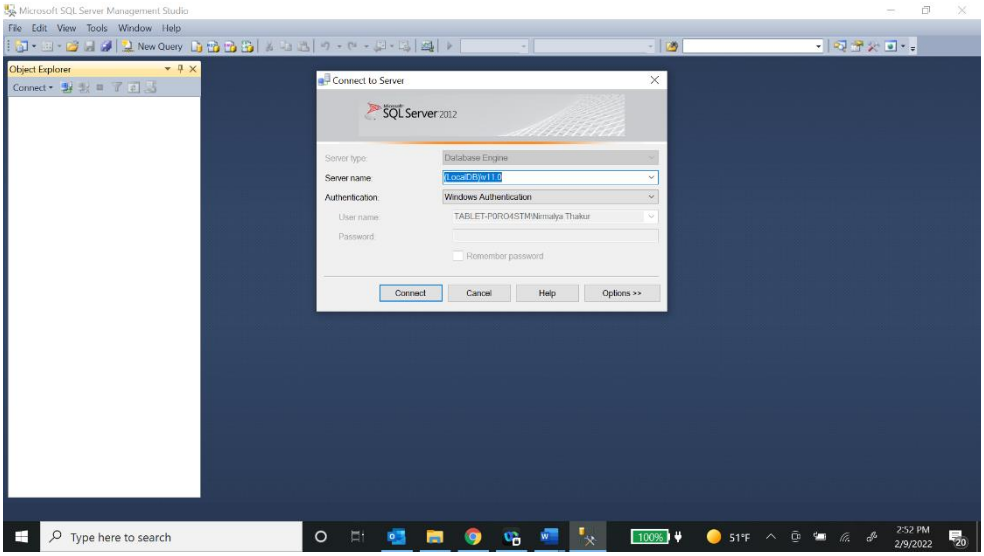

Figure 21. Screenshot from the SQL Server 2012 version that was used for the development of this dataset

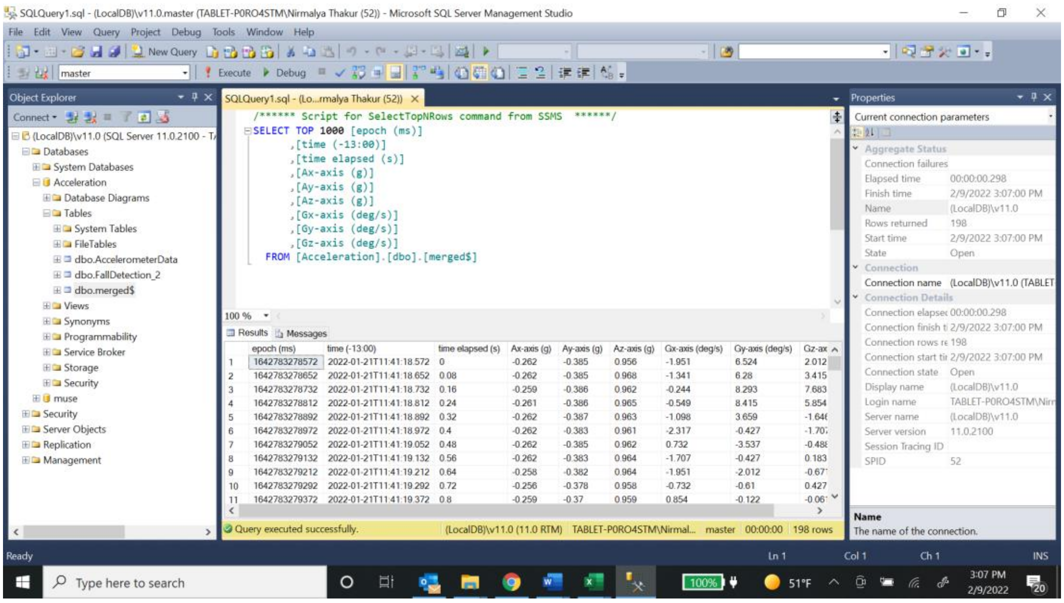

Figure 22. Screenshot from the database table in MS SQL Server 2012 version that represents the data collected from different participants during the experimental trials.

In the upper part of Figure 22, the SQL Query is represented that was used to query the developed database. In the lower part of Figure 22, the specific attributes that comprise this dataset are represented. The image shows only the first 11 rows for clarity of representation. The first two attributes represent the time instants. The third attribute represents the time elapsed (in seconds) for the specific behavioral pattern under consideration. The fourth, fifth, and sixth attributes represent the acceleration data recorded along the X, Y, and Z directions for the specific behavioral pattern under consideration. Similarly, the seventh, eighth, and ninth attributes present the gyroscope data recorded along the X, Y, and Z directions for the specific behavioral pattern under consideration.

Figures 23 and 24 represent the variation of the acceleration data and gyroscope data (in X, Y, and Z directions), respectively, during the different behavioral patterns associated with these ADLs that were performed in different 'activity-based zones' at different time instants by different participants. The data analysis to study this variation was performed in RapidMiner [62]. In both these figures, only a few timestamps are shown for clarity of representation.

Figure 23. Variation of the acceleration data (in X, Y, and Z directions) during the different behavioral patterns associated with these ADLs that were performed in different 'activity-based zones' at different time instants.

Figure 24. Variation of the gyroscope data (in X, Y, and Z directions) during the different behavioral patterns associated with these ADLs that were performed in different 'activity-based zones' at different time instants.

The data successfully collected from the different sensors during the different ADLs performed by the participants and the successful integration of the same towards the development of this database upholds the relevance and effectiveness of this proposed design methodology. These attributes of this database are the exact same attributes that would be necessary for the fall detection and indoor localization systems (described in Sections 3.1 and 3.2, respectively) to funtion together in real-time. This upholds the relevance of the proposed design paradigm and software solution for tracking of the necessary user interaction and user behavior-related data that would be necessary for the development of such systems in real-world environments. The cost-effective nature of the system design described in Table 1 further upholds the fact that it can be easily implemented in the future of IoT-based living environments for the development of such ambient intelligence-based systems to support assisted living of the elderly.

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5. Conclusions and Future Work

As the population ages, modern society is facing a wide range of difficulties stemming from numerous conditions and needs associated with the elderly. Over the last few years, the aging populations throughout the globe have had to contend with a decrease of caregivers to care for them, which has created a variety of difficulties related to independence in carrying out ADLs, which are crucial for one's sustenance. Falls are highly common in the elderly on account of the various bodily limitations, challenges, declining abilities, and decreasing skills that they face with increasing age. Falls can have a variety of negative effects on the health, well-being, and quality of life of the elderly, including restricting their capability to perform or complete ADLs. Falls can even lead to permanent disabilities or death in the absence of timely care and services. To detect these dynamic and diversified needs of the elderly that usually arise in the context of their living environments during ADLs, tracking, and analysis of the spatial and contextual data associated with these activities, or in other words, indoor localization, becomes very crucial.

Despite several works in the fields of fall detection and indoor localization, there exist multiple challenges centered around (1) lack of fall detection systems to perform indoor localization and vice versa; (2) high cost associated with the real-time development and deployment of the underlining systems; (3) development of the systems requiring multiple hardware components which could be difficult to deploy in different environments as well as can get rejected by the elderly; (4) multiple frameworks lacking real-world evaluations; and (5) the underlining systems requiring the development of new devices or gadgets for their implementation which might be difficult to seamlessly replicate in large numbers in multiple real-world environments. To address these challenges, this work proposes a simplistic design paradigm for the development of an ambient intelligence-based living environment with functionalities to perform indoor localization and fall detection. The hardware necessary for the development of this system involves integration of easily available sensors, the combined cost of which is USD 262.15 – which upholds its cost-effectiveness as compared to prior works in this field. The results from real-world experiments uphold the effectiveness of the system design to capture the data that is necessary for the detection of falls as well as for tracking the indoor location of the users while meeting the necessary functionalities in a cost-effective manner. Future work along these lines would involve the development of a stored procedure in the MS SQL Server that would run each time a new row is added in real-time to the database and classify the behavior as a fall or not a fall while tracking the indoor location of the user. This data would then be updated in the database in the form of two new attributes. The working of the stored procedure and the associated software to communicate with these sensors can thereafter be incorporated into a wearable device or gadget that can be worn by the elderly.

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Informed Consent Statement: All subjects gave their informed consent for inclusion before they participated in the study.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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