An Ultrasonic-Based Sensor System for Elderly Fall Monitoring in a Smart Room

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To reduce the risk of elderly people falling in a private room without relying on a closed-circuit television system that results in serious privacy and trust concerns, a fall monitoring system that protects the privacy and does not monitor a person’s activities is needed. An ultrasonic-based sensor system for elderly fall monitoring in a smart room is proposed in this study. An array of ultrasonic sensors, whose ranges are designed to cover the room space, are initially installed on a wall of the room, and the sensors are rotated to transmit and receive ultrasonic signals to measure the distances to a moving object while preventing ultrasonic signal interference. Distance changes measured by ultrasonic sensors are used as time-independent patterns to recognize when an elderly person falls. To evaluate the performance of the proposed system, a sensor system prototype using long short-term memory was constructed, and experiments with 25 participants were performed. An accuracy of approximately 98% was achieved in this experiment using the proposed method, which was a slight improvement over that of the conventional method.

1. Introduction

The world population, which was approximately 7.7 billion people in mid-2019, is gradually increased [1]. The number of elderly people will dramatically rise to approximately 11.1%–18.6% of the total population in the next 30 years [2] due to successful birth control policies and advanced medical care services. As a result, the ratio of the working population to the elderly population is rapidly decreasing. This will lead to a worldwide labor shortage for many industries, including elderly care. At the beginning of the twenty-first century, the European commissioner launched a project called the TeleCARE consortium [3] to design and develop a virtual community infrastructure platform for elderly support. Many other countries in other regions also launched similar projects.

In the community infrastructure, the bedroom, living room, and restroom are the main rooms where elderly people spend most of their time, especially when they are at home, and it is assumed that during this time, privacy is preferred [4]. As elderly individuals are more susceptible to fatal fall [5], they need immediate assistance when a fall occurs. Therefore, automatic fall detection and alarm systems, which are used instead of caregivers to continuously monitor elderly individuals in rooms, must be developed under the conditions of privacy and trust.

The authors of this study proposed the development of an elderly fall monitoring system that can be installed in a private room. The basic conditions of this system include trust, privacy, and safety. We attempted to utilize ultrasonic sensor arrays installed on the ceiling and walls of a room to detect human falls, and experiments were performed with a static model [6–8]. A small room (30 × 30 cm²) with nine ultrasonic sensors was used to test the static model [6]. Ultrasonic interference between neighboring sensors and sensor calibration were found to be problems. These problems were considered, and the sensors were adjusted to mitigate interference [7]. However, coverage gaps between neighboring sensors in the array were found. The overlap of neighboring sensors was proposed to address these gaps, and
experiments were performed using the model in a larger room (60 × 60 cm²) [8]. It was confirmed that the methods proposed in this study could be used to recognize falls using a static model. We also attempted to construct a prototype system for human fall detection. The duration of a fall is approximately 0.7 s. Accordingly, the system must be improved to be able to complete all required processes during this short period of time. Therefore, we reconsidered the system with respect to the hardware and software, improved the hardware, installed an ultrasonic sensor on a sidewall, and developed an algorithm to sense distances to humans in a point-by-point manner to detect falls using the state transition concept without identifying the specific behaviors of the person.

This study is organized as follows. The related works and smart room scenario, including the analysis of ultrasonic array sensors, are presented in Sections 2 and 3, respectively. Our proposed design method is described in Section 3. Experiments and results are reported in Section 4, and a discussion is presented in Section 5. Finally, the study is concluded in Section 6.

2. Related Works

Based on the research problem of elderly fall detection, many researchers have attempted to develop algorithms and systems to monitor elderly individuals and detect their falls. As shown in Table 1, research works related to the development of fall detection systems are generally divided into three approaches [37, 38]: vision-based approaches [14–20, 39–41], wearable device approaches [21–38], and ambience sensor approaches [6–8, 39–41, 42–69]. The vision-based approach is considered an excellent approach due to the beneficial 3D shape information it provides. Accurate results have also been achieved using the wearable device approach because of the dynamic personal position information obtained. Due to the sensors and their locations, sensed information using ambience sensor approaches is mainly a point-to-point approach, which is a limitation. However, the methods in this group were not originally utilized to clearly recognize an object shape. Therefore, these methods are considered to better protect resident privacy.

Previous fall detection systems using ambience devices, including infrared (IR) [39–41], IR and ultrasonic [42, 43], radar [44–51], Wi-Fi [52–57], sound [58–62], and ultrasonic [49–55] systems, have been developed, and their advantages and disadvantages are discussed as follows. IR is mainly used to confirm the absence of objects [39–41, 42, 43], but it cannot be used to measure distance, which makes 3D reconstruction difficult. Moreover, IR has been proven to be harmful to the human eyes and body [39–41, 42, 43]. As it is widely used, Wi-Fi is convenient. Radar is an excellent technique for scanning moving objects for a long time. However, both Wi-Fi and radar operate at high frequencies, which harm the human body and especially affect heart attack patients who use pacemakers [63, 64].

Other than the hearable frequency range, which causes noise harm, sound does not cause any serious harm to the human body. Furthermore, the humans cannot hear an ultrasonic sound. Therefore, sound can be safely used to measure distance using its reflected wavelength [65]. As ultrasonic sound is comparatively safe for the human body, it is recommended in this study as a good technology to develop an automatic fall detection system. In fact, ultrasonic signals, which are mainly applied in point-to-point distance measurements by directional characters, currently cannot be developed at a high resolution for object recognition due to the constraints of its beam. This observation is conversely a merit for this research problem, since, in general, elderly people prefer privacy in their living environment. The ultrasonic sensor becomes a solution to the research problem.

In the research and development of the automatic fall detection systems related to ultrasonic sensors, as shown in Table 2, Toshio Hori et al. [66] presented ultrasonic sensors, which utilized the speed of falling in a vertical direction, for elderly people and their caregivers in a nursing home. This method worked, especially in vertical falling applications, but might not be suitable for some complicated cases of diagonal falling, which is a limitation. Yirui Huang et al. [67] suggested a method to detect falls and remote activity using ultrasonic sensors. This method focused on a cost-effective and intelligent hardware design for individual ultrasonic sensors. This method also utilized the speed and level of falling in each sensor so that it was not matched with complicated fall patterns. Chang and Shih [68] proposed human fall detection based on event pattern matching with ultrasonic array sensors. This method may be used to detect many human fall patterns. However, the sensors were installed at the height of the human leg, which may not be robust enough to detect all fall patterns. Ghosh et al. [69] proposed UltraSense, which is used to identify human activity using a heterogenous ultrasonic sensor grid for smart home environments. This system identified human activity well, which is not preferred from a privacy viewpoint. Moreover, the ultrasonic sensor grid was installed on the ceiling of the room. Since height information is used, the difference between a fall and some normal activities in the vertical direction may confuse the system.

3. Smart Room Scenario

According to statistical data from the United Nations (UN) in 2019 [70], all societies in the world are in the midst of a “longevity revolution,” and the number of elderly people worldwide has dramatically increased year by year. In addition, children and relatives who may closely care for elderly family members do not reside with them in the same household. Approximately half of adults aged 60 and older live alone and approximately one-third live with a spouse only (without children or relatives) in North America and Europe [71]. When an elderly person on their own has a vital accident, such as a fall, it is difficult to obtain assistance as other people may not have noticed that the accident occurred. Unless someone notices and helps the person in a timely manner, an unexpected death may occur.

To solve this problem, an automatic monitoring system that protects user privacy and does not monitor activities
## Table 1: Research works related to image-based and wearable fall detection systems.

| Algorithm name | Sensor and equipment | Feature extraction technique | Classification algorithm | Accuracy/error |
|----------------|----------------------|-----------------------------|--------------------------|----------------|
| **1. Image-based fall detection systems** |
| Hernandez [11] | 2D camera and OpenCV | Rectangle enclosing | Threshold-based | Accuracy 85.37% |
| Lin [12] | GMM and MHI | Acceleration and angular acceleration | Accurately model an ellipse | — |
| Basavaraj [13] | MHI and ellipse approximation | Both ellipse approximation and MHI | Accurately model an ellipse | Accuracy 86.66% |
| ShanShan [14] | Semi-contour distances | Points on the vertical line | SVM | — |
| Chen [15] | Depth camera | Histogram of oriented gradient (HOG) | SVM and ANN | Sensitivity 77.98%, specificity 87.58%, accuracy 82.84% |
| Cai [16] | Optical flow combining with wide residual network | Optical flow and residual network | Softmax classifier | Accuracy 92.6% |
| Marcos [17] | Transfer learning, optical flow algorithm | Displacement vector optical flow algorithm | Fully connected neural network | Sensitivity 95%, specificity 96% |
| Lu [18] | 3D CNN was used | Temporal motion feature, 3D CNN | SVM | Accuracy 99.3% |
| Miguel [19] | Low-cost device, Raspberry Pi | Background subtraction Kalman filter | KNN | Sensitivity 96% specificity 97% |
| Lotfi [20] | Major and minor semi-axis of ellipse fitting silhouette | Spatiotemporal | Multilayer perceptron neural network | Accuracy 99.2%, sensitivity 99.5%, specificity 97.3% |
| **2. Wearable fall detection systems** |
| Freitas [21] | BLE module and a microprocessor | Acceleration | Fall signal to Web app | — |
| Pierleoni [22] | Magnetic, angular rate, and gravity (MARG) sensor | Yaw, pitch, and roll, Madgwick orientation filter | Threshold and SVM | Accuracy 90.37%, sensitivity 80.74%, Accuracy 97.40%, sensitivity 99.48% |
| Otanasap [23] | Using tri-dimensional accelerometer | Acceleration, ADL value | Dynamic threshold model | Accuracy fall forward 95%, accuracy fall backward 75% |
| Kurniawan [24] | Using tri-dimensional accelerometer | Yaw, pitch, and roll, alpha | SVM | — |
| Chu [25] | Wearable device that combined BLE | Acceleration | Exponential smoothing gray model (ESGM) | SVM | Accuracy 96.67%, Sensitivity 90% and specificity 86.7% |
| Shahiduzzaman [26] | Smart helmet | Biomedical sensing data | Threshold-based | Fourfold cross-validation, 13-dimensional |
| Nari [27] | Accelerometer and gyroscope | ACC and gyro | SVM | Accuracy 97.15%, sensitivity 99.17% |
| Nho [28] | Heart rate sensor and accelerometer | Cluster analysis-based user-adaptive fall detection | SVM | Accuracy 97.51% |
| Chen [29] | Crowdsourcing-based adaptive datasets | Acceleration, inclination angle | Threshold-based | Accuracy 97% |
| Tang [30] | Radar sensors on shoe | Distance-to-obstacle | Threshold-based | Extended nearest neighbor | Accuracy 91.73% |
| Djelouat [31] | Compressed sensing | Acceleration | Multilevel fuzzy min-max neural network | SVM | Accuracy 97.29%, specificity 98.7% |
| Jahanjoo [32] | Neural network classification algorithm | 43 features, FFT, principal component analysis | SVM | Accuracy 100% sensitivity 100% |
| Mao [33] | Magnetometer and gyroscope | Acceleration, Euler angle (orientation) | SVM | Threshold-based |
| Ang [34] | Multiple power-saving algorithms | Acceleration | Decision tree classifier | Sensitivity 91% |
| Purushothaman [35] | A neural network classification algorithm | Linear and angular acceleration | Neural network | — |
| Khojasteh [36] | Threshold optimization | Eight features from acceleration | SVM, RBS, and DT | Accuracy 95.15% |
| De Quadros [37] | Madgwick’s decomposition | Statistical features from acceleration | SVM-KNN with Madgwick’s decomposition | Sensitivity 93%, specificity 98% |
| Saleh [38] | Two-segment feature extraction | Statistical 12 feature vectors from acceleration | Artificial neural network and SVM | Accuracy 99.9%, sensitivity 99.1%, specificity 99.9% |
should be installed in every house. In addition, the system must provide an immediate alert whenever a fall occurs. In our proposed scenario, an automatic monitoring system, with sensors and devices that do not directly visually recognize and record activities, is installed on the wall of a room. Therefore, an ultrasonic node was selected as the sensor in this study to continuously measure distances from the ultrasonic nodes to the person in the room in a point-to-point manner.

### Table 2: Research works in ambience sensor-based systems.

| Algorithm name | Sensor and equipment | Feature extraction technique | Classification algorithm | Accuracy/error |
|----------------|----------------------|------------------------------|--------------------------|----------------|
| 1.1 IR sensor | Floor pressure and infrared image | Average image pixel value (mean) | Image thresholding | Accuracy 98.3% |
| Tzeng [39] | | | | |
| Guan [40] | Infrared signal-based | Multi-sensor time | K-nearest neighbor, GM-HMM, SVM | Sensitivity 98%, specificity 93% |
| Ogawa [41] | IR array sensor | Temperature distribution × 20 | Machine learning | Accuracy 97.75% |
| Ashbørn [42] | IR array sensor | 80 × 60 thermal array | Multilayer perceptron model | Accuracy 96.73% |
| Chen [43] | Infrared arrays and ultrasonic | 8 × 8-pixel thermal, RMS values | SVM | Accuracy 90.3% |
| 1.2 Radar sensor | | | |
| | | | |
| 1.3 Wi-Fi device | Wi-Fi device | Channel state information (CSI) | SVM | Sensitivity 92%, specificity 92% |
| Wang [52] | | | | |
| Khan [53] | Passive Wi-Fi sensing, Vi Wi | Two-dimensional phase extraction system | Tremor classification | Accuracy 98% |
| Gu [54] | Wi-Fi device | Channel state information (CSI) | Activity recognition | Accuracy 94.58% |
| Ramezani [55] | Wi-Fi, accelerometer, and floor vibration | CSI, STD, MAD, IR, SRS | SVM | — |
| Cheng [56] | Wi-Fi signals | Channel state information (CSI) | CNN, LSTM, GRU | — |
| Hu [57] | Wi-Fi | Channel state information (CSI) | SLN-DTW | Accuracy 96% |
| 1.4 Acoustic sensor | Acoustic signal | Pattern recognition, event segmentation | Event classification | — |
| Zigel [58] | | | | |
| Li [59] | Circular array of 8 microphones | MFCC | Nearest neighbor | AROC 0.98 |
| Li [60] | Beamforming to increase signal strength | MFCC | Nearest neighbor | Sensitivity 100%, specificity 97% |
| Li [61] | 8-Microphone circular array | iVAT clustering and GA-based | Nearest neighbor | — |
| Cheffena [62] | Smartphone | The spectrogram, MFCCs, LPC, and MP | ANN | Accuracy 98% |
| 1.5 Ultrasonic sensor | Ultrasonic sensor network and floor mat sensor | Tracking a head of moving human | Pattern trajectories | — |
| Yoshio [66] | | | | |
| Huang [67] | Ultrasonic sensor array, FPGA | Distance, time duration | Pattern matching | — |
| Chang et al. [68] | Arduino ultrasonic array | Time energy | SVM | Accuracy 98% |
| Nadee et al. [6] | Ultrasonic array: ceiling, sidewall | Distance, time duration | Threshold-based algorithm | Accuracy 92% |
| Nadee et al. [7] | Ultrasonic array: two temperature sensor error correction | Distance, time duration | Threshold-based algorithm | Accuracy 93% |
| Nadee et al. [8] | Ultrasonic array: octagonal array | Distance, time duration | Threshold-based algorithm | Accuracy 94% |
| Ghosh et al. [69] | HC-SR04, LV-MaxSonar-EZ0 sensor | Distance, time duration | Decision tree | Accuracy 90% |
| This work | Ultrasonic array: MaxSonar MB1010 | Distance, time duration | LSTM | Accuracy 98% |
point manner. In addition, external memory, which can store data permanently, is not utilized in this system to protect activity data. As shown in Figure 1, the fall monitoring system consists of a processor, microcontroller, and sensors that are installed in a room, which is called a smart room in this study. The system may immediately alert caregivers, relatives, and children via Wi-Fi, the cloud, and mobile phones whenever a fall occurs.

Based on the scenario of a smart room for elderly people, privacy-based and distance-based human fall detection and sensor blind zone are analyzed as follows.

3.1. Privacy-Based Human Fall Detection. According to the studies in [72], the human body comprises moving-independent parts or modules, and a point located on a module called a control point can represent the module position, as shown on the right side of Figure 1. If a control point representing a module is detected and the distances from the sensors to the control points are measured, the body of a person is detected and monitored. Therefore, the patterns of control points when a fall occurs (e.g., a forward fall, a backward fall, a sideways fall, and a fall from a chair) can be observed and analyzed, as shown in Figure 2. These patterns can be trained in advance and can possibly be used to recognize falls in elderly fall monitoring systems. Although the control points of a person do not show real pictures such as a video clip captured by a closed-circuit television (CCTV), it may be possible to estimate the behaviors of the person even by the control point image. Elderly people may prefer that activities done during their private time are not monitored, as an absolute condition to develop the fall monitoring system.

Suppose that a video clip and an image of control points of humans are not allowed to be used as input data in the fall monitoring system. Instead, a point representing human body movement per frame, which contains the least amount of data in a frame and from which, it is almost impossible to determine activities, should be considered to enable fall recognition. During a fall, a point that is closest to a sensor is sensed, and this sensor may change based on the movement of the falling person. Distances from those points closest to a sensor that is continuously collecting information during a fall can be categorized into patterns based on the type of fall. Figures 3(a)–3(d) show some examples of video frames (upper row) and distances between sensors and a person (represented as a graph). The distance changes during a fall based on different fall types, e.g., forward, backward, and sideways falls and a fall from a chair, can be differentiated as patterns in the graph. These different patterns can be used to classify a fall and a nonfall as well as recognize fall types. If a classifier is trained with these distance change patterns in advance, pattern matching between these trained patterns and input data can always be used to classify the input as either a fall or a nonfall.

3.2. Distance-Based Human Fall Detection. To apply the abovementioned concept to the human fall problem, since the time period for a human fall is as short as approximately 0.7 s [72], the whole room space should be sensed and
monitored so that the fall detection system can be pro-
cessed and an alarm immediately activated during this 
period. In the case that a distance sensor is installed on a 
sidewall to measure the shortest distance from a sensor to a 
human at a point \(s\) in the room space, as shown in 
Figure 4, the change in measured distances during the fall 
duration \(T_{fl}\) is mathematically expressed as the following 
fall pattern \(F\).

\[
F = \int_{T_{fl}}^{T_{fl+1}} f(s) \, dt.
\]  

(1)

To cover the whole room space with ultrasonic signals 
without interference, multiple sensors are installed in an 
orderly manner in a matrix form, as shown in Figure 5. In 
this case, coverage ranges almost cover the sensing wall, but 
blind spaces or gaps exist between neighboring cells. To fill in 
the blind spaces, ultrasonic nodes should be shifted in an 
orderly manner along a straight line and simultaneously the 
given distance between consecutive ultrasonic nodes should 
be maintained to prevent interference, as shown in 
Figure 6(a). Additionally, the sensors can also be shifted in 
zigzag scanning lines to maintain balance in the horizontal 
and vertical directions. As an example, an ultrasonic node or 
more than one ultrasonic node can be scanned along a zigzag 
line, as illustrated by the black and red dashed arrows in 
Figure 6(b).
ultrasonic rays at a distance smaller than the width of the human as the design condition. This guarantees the detection of human falls even in a blind zone. Thus, the range \(d\) between consecutive ultrasonic nodes can be obtained.

\[
d = \frac{B \times 2 \cos(90 - \theta/2)}{\cos(\theta/2)}.
\]  

In addition, the power transmitted by a string wave \(E\) can be determined as follows [73, 74]:

\[
E = \frac{1}{2} \left(\mu \omega^2 A^2 \nu\right) = 2 \mu \pi^2 f^2 A^2 \nu,
\]

where \(\mu, \omega, A, \) and \(\nu\) represent the mass per unit length of the string, angular frequency of the wave, wave amplitude, and wave propagation velocity, respectively.

## 4. Proposed Ultrasonic-Based Human Fall Monitoring System

Based on the abovementioned concept, a fall detection design and implementation method using ultrasonic sensors for the monitoring system is explained in this section. It is assumed that the system must be not only nonintrusive, noninvasive, and device-free but also protect the user’s privacy. In the following, the system design and implementation are divided into hardware and software parts.

### 4.1. Hardware Design

The hardware system mainly consists of two units, a sensor array and a signal processing unit. The sensor array installed on a wall must be designed to cover the whole room with the smallest blind zone. In addition, the signal processing unit must provide enough ports for receiving signals from all sensors and must be designed to have enough ability to process those signals. The design of the sensor array and signal processing unit is explained as follows.

#### 4.1.1. Sensor Array

Suppose the scale of a room in which the ultrasonic sensor array for the human fall monitoring system is installed is \(M \times N \times l\). Ultrasonic sensor nodes should be geometrically installed on a sensor wall \((M \times N)\) in the room under the condition of noninterference. The range between consecutive ultrasonic nodes in the horizontal \((\varphi_N)\) and vertical \((\varphi_M)\) directions can be simply determined.

\[
\varphi_N \geq 2l \tan \frac{\theta}{2}, \quad \varphi_M \geq 2l \tan \frac{\theta}{2}.
\]  

If \(B\) represents the blind zone for human sensing, which has to be determined in advance, the range between consecutive sensors in the array \(d\) can be obtained based on (5).

In the first step, the number of sensors in the horizontal \((\partial_N)\) and vertical \((\partial_M)\) directions for sensing the distance in a frame, which must be limited due to the interference of ultrasonic signals from different sensors in a frame, can be simply determined.
Based on our proposed concept to shift the active sensors in the dense ultrasonic sensor array instead of dynamically scanning the ultrasonic sensors, the time duration for shifting mainly depends on the average human fall duration ($T_{fl}$). If a sensing process takes a duration of time ($T_u$), a shifting range ($d$), which is regarded as the dense sensor node range, can be calculated.

$$d = k\left(\frac{T_{fl}}{T_u}\right).$$  \hfill (9)

The total number of dense node sensors ($S_i$) is therefore determined.

$$S_i = \frac{M \times N}{d^2}. \hfill (10)$$

### 4.1.2. Signal Processing Unit

The signal processing unit consists of a power supply unit, an ultrasonic sensor array, a microprocessor, memory, and a classifier, as shown in Figure 8. The ultrasonic sensor array, which is supplied power by the power supply unit, always senses a moving object in the room. Analog signals representing the distance from ultrasonic sensors to a moving object are transmitted to the microprocessor. In the microprocessor, the analog signals are translated into distance data and stored in terms of a matrix in the memory. The matrix of distance data is finally fed to the classifier as a feature for fall classification.

In the power supply unit, the power needed to drive an ultrasonic sensor can be calculated based on equation (6). In equation (6), $\mu, f, A$, and $v$ can be determined as the mass per unit length of the string [75], the frequency of the ultrasonic signal (defined above the sound frequency or set to 20 kHz), the amplitude of the ultrasonic signal, and the ultrasonic velocity [76], respectively.

Since this study proposes the utilization of the change patterns of distance from the ultrasonic sensor nodes to the closest point of a person who has fallen, the ultrasonic signals should be transmitted to reflect the falling person in as many round trips as possible. The number of scanning frames ($\tau$) for ultrasonic signal transmission in one second can be simply estimated:
where $v$, $P$, and $l$ are the ultrasonic signal velocity, frequency, processing time, and room depth, respectively.

In human fall detection and classification, the number of scanning frames is one of the crucial keys to fundamentally guaranteeing quality. The number of scanning frames is practically an initial condition to design the signal processing unit. Although the more scanning frames there are, the more robust the system is, and users may select an appropriate set of devices that is normally limited by processing time. For example, the processing time of a frame is limited on an approach of real time. Thus, the number of scanning frames should be calculated in real time during the period of a human falling, which is approximately 0.7 s. Suppose users fix the number of scanning frames, the maximum processing time allowed in each frame is what users may need next to select electronic devices in the hardware design step. Thus, users can expect to be able to select devices by specifications based on the allowed processing time. The processing time per frame ($P$) of devices allowed in the system design can be calculated.

$$P = \frac{N_t \cdot 2l}{\tau} - \frac{2l}{v},$$

where $v$, $\tau$, and $l$ are the ultrasonic signal velocity, frequency, number of scanning frames, and room depth, respectively.

### 4.2. Software Design

The software system for retrieving ultrasonic signals representing the distance to a moving object can be designed and created, as shown in Algorithm 1. First, the initialization and declaration of variables are registered for values measured by the sensors and shown in steps 2–4. Then, an infinite loop (steps 5–14) is run to read a distance value on an ultrasonic sensor, store it in a matrix, shift the active sensor to another neighboring sensor according to the zigzag direction in Step 6 for all sensor nodes, and then classify the fall. The 2D matrix of distances in Step 6 is converted into a 1D matrix in steps 7–12, and it is fed to a classifier for fall classification in Step 13. The details of the rotation of active ultrasonic sensors and fall classification are explained in Sections 4.2.1 and 4.2.2, respectively.

#### 4.2.1. Rotation of Active Ultrasonic Sensors

To implement a software unit of the fall monitoring system, multiple ultrasonic nodes in an array are expected to simultaneously sense distances from the sensors to objects. However, interferences among ultrasonic signals may occur and lead to errors in the case where coverage areas overlap. To prevent ultrasonic signal interference, coverage areas must not overlap. The possible number of ultrasonic nodes for the simultaneous distance measurement can be determined by the minimum distance between working ultrasonic nodes, as shown in equation (7). To efficiently scan ultrasonic nodes in an array by maintaining a minimum distance, zigzag scanning is recommended to balance the horizontal and vertical directions; notably, zigzag scanning is demonstrated for a pair of ultrasonic nodes in Figure 8. Suppose that a couple of scanning lines on ultrasonic nodes in an array simultaneously start from points A and B; they synchronously move along a zigzag scanning line to the next nodes, which are labeled in the same colors. If the coordinates of ultrasonic sensor nodes are represented by row ($R$), column ($C$), and current node counting ($i$), patterns of nodes moving in a couple of zigzag scanning lines (A and B) can be logically illustrated by rows ($R_A$, $R_B$) and columns ($C_A$, $C_B$) of A and B.

**Group 1.** Shift from the first node (represented by a scanning line A in Figure 9)

Initially, the scanning node will be shifted to the adjacent node in the edge row as initial couple nodes. This logic can be simply expressed as follows.

**Pattern a:**

\[
\begin{align*}
\text{IF} \quad I &= 0 \quad \text{THEN} \quad R_A(i+1) = R_A(i), \quad C_A(i+1) = C_A(i) + 1, \\
&\quad \text{A}: \text{Shift straight right.} \quad R_B(i+1) = R_B(i) + 1, \quad C_B(i+1) = C_B(i) - 1, \\
&\quad \text{B}: \text{Shift diagonally left down}
\end{align*}
\]
Figure 9: Zigzag scanning patterns for a pair of ultrasonic nodes.

**Group 2.** Cases where the current sensing node is located in the 0th row ($R_A(i) = 0$); Subgroup 2.1 Shift in the diagonal down direction (b on scanning line A in Figure 9)

When the previous sensing node ($R_A(i–1)$, $C_A(i–1)$) located in the 0th row is shifted right to the current sensing node ($R_A(i)$, $C_A(i)$) located in the 0th column, the next sensing node ($R_A(i)$, $C_A(i)$) will be shifted down in the diagonal direction. This logic can be expressed as follows.

**Pattern b:**

IF $[R_A(i) = 0]$ and $|[R_A(i) − R_A(i–1)| = odd ] and $[|C_A(i) − C_A(i–1)| | = even]$

THEN $R_A(i+1) = R_A(i) + 1$, $C_A(i+1) = C_A(i) + 1$. Shift diagonally left down

$R_B(i+1) = R_B(i) + 1$, $C_B(i+1) = C_B(i)$. Shift right

Subgroup 2.2. Shift right on the 0th row (f on scanning line A in Figure 9)

When the previous sensing node ($R_A(i–1)$, $C_A(i–1)$) located outside of the 0th row approaches the current sensing node ($R_A(i)$, $C_A(i)$), the next sensing node ($R_A(i+1)$, $C_A(i+1)$) will be shifted right on the 0th row. This logic can be expressed as follows.

**Pattern c:**

IF $[R_A(i) = 0]$ and $|[R_A(i) − R_A(i–1)| = odd ] and $[|C_A(i) − C_A(i–1)| | = even]$

THEN $R_A(i+1) = R_A(i)$, $C_A(i+1) = C_A(i) + 1$. Shift right

$R_B(i+1) = R_B(i) + 1$, $C_B(i+1) = C_B(i) − 1$. Shift diagonally left down

**Group 3.** Cases where the current sensing node is located in the 0th column ($C_A(i) = 0$); Subgroup 3.1 Shift down on the 0th column (c on scanning line A in Figure 9)

When the previous sensing node ($R(i–1)$, $C(i–1)$) located out of the 0th column approaches the current sensing node ($R(i)$, $C(i)$) located on the 0th column, the next sensing node ($R(i+1)$, $C(i+1)$) will be shifted down on the 0th column. This logic can be expressed as follows.

**Pattern d:**

IF $[C_A(i) = 0]$ and $|[R_A(i) − R_A(i–1)| = odd ] and $[|C_A(i) − C_A(i–1)| | = even]$

THEN $R_A(i+1) = R_A(i)+1$, $C_A(i+1) = C_A(i)$. Shift down

$R_B(i+1) = R_B(i) − 1$, $C_B(i+1) = C_B(i) + 1$. Shift diagonally right

Shift in diagonal right up direction (d on scanning line A in Figure 9)

When the previous sensing node ($R(i–1)$, $C(i–1)$) located out of the 0th column is shifted down to the current sensing node ($R(i)$, $C(i)$) located on the 0th column, the next sensing node ($R(i+1)$, $C(i+1)$) will be shifted up in the diagonal direction. This logic can be expressed as follows.

**Pattern e:**

IF $[C_A(i) = 0]$ and $|[R_A(i) − R_A(i–1)| = odd ] and $[|C_A(i) − C_A(i–1)| | = even]$

THEN $R_A(i+1) = R_A(i) − 1$, $C_A(i+1) = C_A(i) + 1$. Shift diagonally right

$R_B(i+1) = R_B(i) − 1$, $C_B(i+1) = C_B(i) + 1$. Shift diagonally right

**Group 4.** Cases where the current sensing node is not located on the edge ($C_A(i)$ $≠$ 0 and $R_A(i)$ $≠$ 0; Subgroup 4.1 Shift in the diagonal right direction (e on scanning line A in Figure 9)

When the previous sensing node ($R_A(i–1)$, $C_A(i–1)$) is shifted diagonal right up to the current sensing node ($R_A(i)$, $C_A(i)$) located out of the 0th column and out of the 0th row, the next sensing node ($R_A(i)$, $C_A(i)$) will be shifted up in the diagonal direction. The logic can be expressed as follows.

**Pattern f:**

IF $[C_A(i) ≠ 0]$ and $|[R_A(i) − R_A(i–1)| = odd ] and $|[R_A(i) − R_A(i–1)| = odd]$

THEN $R_A(i+1) = R_A(i)$, $C_A(i+1) = C_A(i)+1$. Shift diagonal up.

$R_B(i+1) = R_B(i)+1$, $C_B(i+1) = C_B(i)$. Shift down

Subgroup 4.2. Shift in the diagonal left direction

When the previous sensing node ($R_A(i–1)$, $C_A(i–1)$) is shifted diagonal right up to the current sensing node ($R_A(i)$, $CA(i)$) located out of the 0th column and out of the 0th row, the next sensing node ($R_A(i)$, $C_A(i)$) will be shifted down in the diagonal direction. This logic can be expressed as follows.

**Pattern g:**

IF $[C_A(i) ≠ 0]$ and $|[R_A(i) − R_A(i–1)| = odd ] and $|[R_A(i) − R_A(i–1)| = odd]$

THEN $R_A(i+1) = R_A(i) + 1$, $C_A(i+1) = C_A(i) − 1$. Shift diagonally left down.

$R_B(i+1) = R_B(i) − 1$, $C_B(i+1) = C_B(i) + 1$. Shift diagonally right up
Teselogics cover the possible movement of a couple of currentsensing nodes (\(R_A(i)\), \(C_A(i)\)) and (\(R_B(i)\), \(C_B(i)\)) to the next sensing nodes (\(R_A(i+1)\), \(C_A(i+1)\)) and (\(R_B(i+1)\), \(C_B(i+1)\)) in a couple of zigzag scanning lines. As an example, an algorithm for shifting a couple of sensing nodes to the next sensing nodes in a couple of zigzag scanning lines is described in Algorithm 2.

### 4.2.2. Fall Classification

Due to the time limitation and time invariance of a human fall, long short-term memory (LSTM), which is regarded as an excellent classifier for time invariance, is utilized in this study. Distance information from sensors to a human is assumed to be input data for the classifier. As shown in Figure 10, the node number in the input layer is determined based on the number of sensors that sense a moving object during a human fall, which is assumed to take approximately 0.7 s, and the output nodes for the fall detection system should be set as many to one, with a number of preference choices, such as backward fall, forward fall, or walking. The hidden layer of the LSTM is used to set the input size per series to 2/3 of its original value [77].

Pretests must be performed on some samples using possible parameters in the training state to determine the experimental parameter settings. As shown in Table 3, the activation function (e.g., softmax, ReLU, sigmoid, and tanh) should be pretested on some samples in advance and selected appropriately for the networks. In the input layer, the batch size, input size per series, input feature, and learning rate are trained with a number of \(2^n\) within the capability of the graphics processing unit (GPU) memory, total number of input data of all features, input data dimension, and appropriate rate for gradient descent that considers an appropriate time, respectively, without overshooting [78].

### 5. Experiments and Results

To evaluate the performance of the proposed method, a room with ultrasonic sensors installed was constructed, and a data processing system was implemented based on the experimental specifications, as shown in Table 4. For the experiments, a representative group of participants were selected based on sex and age. These participants were trained to walk, sit, and fall in the room before experiments were performed. The LSTM classifier was set up based on the specifications shown in Tables 1 and 2. Photographs of an empty room, a room with a participant, and our design interface with a memory card are shown in Figures 11(a)–11(c), respectively. The experiments were performed by 25 participants using some behavior criteria, including falling, walking, and sitting in the constructed room, as shown in Table 5. The experimental results obtained in distance data of one and two points per frame reveal the human fall recognition rate based on the number of training and testing samples, as shown in Tables 6 and 7, respectively. The results
are divided into the following groups: 20–40 years of age and 41 years of age and older. Training and testing data from the experiment were processed with ratios of 90:10, 80:20, 70:30, 60:40, and 50:50 to access the accuracy of the training and testing criteria. An accuracy of approximately 99.14% was achieved using the ratio of 90:10 after the training and testing experiments. Compared with conventional methods, the proposed method exhibited an improvement in accuracy by approximately 1.14%, as shown in Table 8. Examples of distances captured by two node sensors in the cases of a forward fall, backward fall, fall from a chair, and walking are given in Table 4.

### Table 4: Experimental specifications.

| Devices/software/participants | Specifications |
|-------------------------------|----------------|
| Computer system               | Aspire VX15    |
| CPU                           | Intel Core i7-7700HQ |
| GPU                           | NVIDIA GeForce GTX 1050 |
| Memory size                   | 12 GB DDR4 |
| Hard disk drive               | SSD 512 GB |
| Basic programming             | MATLAB_R2019b |
| Participants                  | 25 people |
| Age and height ranges of participants | 21–30 years; male: 8; female: 2; 158–175 cm |
|                               | 31–40 years; male: 4; female: 0; 165–178 cm |
|                               | 41–50 years; male: 3; female: 1; 158–175 cm |
|                               | 51–60 years; male: 2; female: 0; 158–175 cm |
|                               | >60 years; male: 3; female: 2; 158–175 cm |
| Experiment 1 (walk)           | Participants: 25 people; 8 groups |
| Experiment 2 (fall)           | Participants: 25 people; 4 groups |
| Room size                     | Size: 200 × 200 cm² |
| Sensors                       | 16 nodes |
| Distance between sensors      | 50 cm |
| Blind spot distance           | 15.2 cm |

### Algorithm 2: Zigzag scanning.

```plaintext
(i) BEGIN
   DATA: i: counting variable
   dis_A, dis_B: distance from A and B
   i = 0
   READ: distances (dis_A[i], dis_B[i]) from A and B
   SHIFT A straight right
   SHIFT B diagonally left down
   CALCULATE: i = i + 1
   READ: DISTANCE distances (dis_A[i], dis_B[i]) from A and B for i = 2 to (N × M/2) − 1 do
   Switch Pattern do
     case b
       SHIFT A diagonally left down
       SHIFT B straight right
     case c
       SHIFT A straight right
       SHIFT B diagonally left down
     case d
       SHIFT A straight down
       SHIFT B diagonally right up
     case e
       SHIFT A diagonally right up
       SHIFT B diagonally right up
     case f
       SHIFT A diagonally right up
       SHIFT B straight down
     case g
       SHIFT A diagonally left down
       SHIFT B diagonally right up
   READ: distance(dis_A[i], dis_B[i])
   END for
   END
```
Ultrasonic sensors
200 cm
200 cm
Signal 
reflection
wall
Analog
A0-A15
Control
signal 
pins
(a) (b) (c)

Figure 11: Photographs of the experiments.

Table 5: Samples for training and testing.

| No. | Posture Category                  | No. of samples |
|-----|-----------------------------------|----------------|
| 1   | Forward fall                      | 100            |
| 2   | Backward fall                     | 100            |
| 3   | Left and right sideways falls     | 100            |
| 4   | Fall from a chair                 | 100            |
| 5   | Walk to chair                     | 25             |
| 6   | Walk to sensor                    | 25             |
| 7   | Walk away from sensor             | 25             |
| 8   | Walk in a circle                  | 25             |
| 9   | Walk left to right                | 25             |
| 10  | Walk right to left                | 25             |
| 11  | Walk diagonal left to right       | 25             |
| 12  | Walk diagonal right to left       | 25             |
|     | Total of samples                  | 600            |

Table 6: Experimental results based on one node.

| Train/test | Recognition (%) | Error (%) | SD | TP |   |   | FP |   | FN |   |   |   |   |   |   |   |
|------------|-----------------|-----------|----|----|---|---|----|---|----|---|---|---|---|---|---|---|
|            | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total |
| 90/10      | 95.74          | 4.26      | 0.52 | 23 | 34 | 57 | 1 | 2 | 3 | 0 | 0 | 0 | |
| 80/20      | 89.58          | 10.42     | 0.56 | 43 | 64 | 107 | 4 | 6 | 10 | 1 | 2 | 3 |
| 70/30      | 86.43          | 13.57     | 0.63 | 62 | 94 | 156 | 7 | 11 | 18 | 3 | 4 | 7 |
| 60/40      | 79.72          | 20.28     | 0.60 | 77 | 114 | 191 | 14 | 24 | 38 | 5 | 6 | 11 |
| 50/50      | 70.33          | 29.67     | 0.65 | 84 | 127 | 211 | 24 | 38 | 62 | 12 | 15 | 27 |

Table 7: Experimental results based on two nodes.

| Train/test | Recognition (%) | Error (%) | SD | TP |   |   | FP |   | FN |   |   |   |   |   |   |   |
|------------|-----------------|-----------|----|----|---|---|----|---|----|---|---|---|---|---|---|---|
|            | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total | Age 20–40 | >40 | Total |
| 90/10      | 98.15          | 1.85      | 0.50 | 24 | 35 | 59 | 0 | 1 | 1 | 0 | 0 | 0 |
| 80/20      | 96.47          | 3.53      | 0.53 | 46 | 70 | 116 | 2 | 2 | 4 | 0 | 0 | 0 |
| 70/30      | 93.43          | 6.57      | 0.57 | 67 | 101 | 168 | 5 | 7 | 12 | 0 | 0 | 0 |
| 60/40      | 90.58          | 9.42      | 0.57 | 88 | 130 | 218 | 7 | 13 | 20 | 1 | 1 | 2 |
| 50/50      | 86.56          | 13.44     | 0.63 | 104 | 156 | 260 | 14 | 21 | 35 | 2 | 3 | 5 |
Table 8: Performance comparison with conventional methods.

| Method               | Recognition ratio (%) | Precision (%) | Recall (%) | SD    |
|----------------------|-----------------------|---------------|------------|-------|
| Huang et al. 2012 [67] | 92                    | —             | —          | —     |
| Chang et al. 2017 [68] | 98                    | —             | —          | —     |
| Ghosh et al. 2019 [69] | 90                    | 74            | 100        | —     |
| Proposed method      | 98.15                 | 98.30         | 100        | 0.500 |

![Figure 12: Distances in fall cases: (a) forward fall, (b) backward fall, (c) sideways fall, (d) fall from a chair, and (e) walking.](image)

during 1,000 ms are shown in Figure 12. These graphs show patterns of distance changes for each case. While ultrasonic signal transmitters are located on a wall scan in the zigzag direction to transmit ultrasonic signals by two nodes each time, distances are always measured by 16 sensors (0,0–3,3) located on the opposite sidewall. All measured distances during 1,000 ms are shown in the graphs. In these measured distance data, differences among a forward fall, backward fall, sideways fall, fall from a chair, and walking were observed. These data were input into the LSTM for training and classification.
In the experiments, the measured distances in continuing frames that showed behaviors, such as falling, walking, and sitting done by the 25 participants (as shown in Table 4), were used to train and test with various ratios. Errors occurred based on the use of one node or two nodes, as shown in Table 9, respectively (Table 10). These errors are analyzed in the discussion.

6. Discussion

To build a smart room that can be used to detect the falls of elderly people without an intrusion of privacy, this study proposes installing an array of ultrasonic sensors on a wall, activating the sensors to sense distance information, and classifying the falls of elderly people based on distance change patterns. The performance of the proposed method was evaluated, and the accuracy was more than 90% in the cases of training more than 50% of the 2 node-based sample data, as shown in Table 7. Based on the results of the 1 node-based data shown in Table 6, the accuracy using this method was worse than that of the 2 node-based data because sensing based on one node was insufficient to cover the whole room. If the room was much smaller so that the range of the ultrasonic signal covered the room, one node would be adequate. Users must consider the coverage range of the ultrasonic signals with respect to the room scale as one of the design conditions. The results shown in Tables 5 and 6 confirm the effective range of sensor coverage and were used to evaluate the performance of the proposed method. Acceptable accuracy was achieved. The accuracy increased according to the increasing ratio of training samples, and an approximately 98% accuracy was achieved using the 90:10 training and testing ratio. Although elderly individuals (individuals over 40 years of age in this experiment) comprehensively caused both positive and negative faults, they contributed a large number of true positives to the results compared with the other group. Therefore, the proposed method was considered to be applicable to elderly individuals. The proposed method was compared with conventional methods, and it was obvious that higher precision and recall were obtained using the proposed method, as shown in Table 8. These high accuracy results were analytically caused by the distance change patterns of forward, backward, and sideways falls, falls from a chair, and especially walking, as shown by the examples in Figure 12. As observed change patterns among consecutive frames in the time domain, classifiers for video were confirmed to be appropriate tools for this kind of fall detection and classification problem.

| Table 9: Error analysis based on one node. |
|-------------------------------------------|
| Ratio of training/testing                  | 90:10 | 80:20 | 70:30 | 60:40 | 50:50 |
| Type                                       |       |       |       |       |       |
|                                           | Correct | Error | Correct | Error | Correct | Error | Correct | Error | Correct | Error |
| Forward fall                              | 10     | 19    | 1      | 24     | 6      | 29     | 11     | 35     | 15    |
| Backward fall                             | 10     | 18    | 2      | 25     | 5      | 33     | 7      | 38     | 12    |
| Left and right sideways fall              | 10     | 17    | 3      | 26     | 4      | 35     | 5      | 33     | 17    |
| Fall from a chair                         | 8      | 2     | 17     | 3      | 24     | 6      | 32     | 8      | 34     | 16    |
| Walk left to right                        | 3      | 5     | 7      | 1      | 7      | 3      | 9      | 4      |
| Walk right to left                        | 2      | 4     | 1      | 7      | 7      | 3      | 9      | 3      |
| Walk in a circle                          | 3      | 4     | 1      | 7      | 1      | 8      | 2      | 10     | 3     |
| Walk diagonal left to right               | 2      | 5     | 7      | 1      | 8      | 2      | 8      | 4      |
| Walk diagonal right to left               | 3      | 3     | 2      | 7      | 1      | 8      | 2      | 7      | 6     |
| Walk to sensor                            | 2      | 5     | 7      | 1      | 8      | 2      | 9      | 3      |
| Walk away from sensor                     | 3      | 5     | 8      | 1      | 9      | 1      | 10     | 3      |
| Walk to chair                             | 2      | 5     | 7      | 1      | 8      | 2      | 9      | 3      |
| Sum                                       | 58     | 2     | 107    | 13     | 156    | 25     | 191    | 49     | 211    | 89    |

| Table 10: Error analysis based on two nodes. |
|----------------------------------------------|
| Ratio of training/testing                    | 90:10 | 80:20 | 70:30 | 60:40 | 50:50 |
| Type                                         |       |       |       |       |       |
|                                             | Correct | Error | Correct | Error | Correct | Error | Correct | Error | Correct | Error |
| Forward fall                                | 10     | 20    | 29     | 1      | 38     | 2      | 47     | 3      |
| Backward fall                               | 10     | 20    | 28     | 2      | 37     | 3      | 46     | 4      |
| Left and right sideways fall                | 10     | 19    | 29     | 1      | 38     | 2      | 46     | 4      |
| Fall from a chair                           | 9      | 1     | 18     | 2      | 28     | 2      | 37     | 3      | 45     | 5     |
| Walk left to right                          | 3      | 5     | 7      | 1      | 8      | 2      | 10     | 3      |
| Walk right to left                          | 2      | 5     | 6      | 1      | 8      | 2      | 9      | 3      |
| Walk in a circle                            | 3      | 5     | 8      | 1      | 9      | 1      | 11     | 2      |
| Walk diagonal left to right                 | 2      | 5     | 6      | 1      | 8      | 2      | 9      | 3      |
| Walk diagonal right to left                 | 3      | 5     | 7      | 1      | 9      | 1      | 10     | 3      |
| Walk to sensor                              | 2      | 5     | 7      | 1      | 10     | 1      | 10     | 2      |
| Walk away from sensor                       | 3      | 5     | 7      | 1      | 8      | 2      | 9      | 4      |
| Walk to chair                               | 2      | 4     | 1      | 6      | 1      | 8      | 2      | 8      | 4     |
| Sum                                        | 59     | 1     | 116    | 4      | 168    | 12     | 218    | 22     | 260    | 40    |
| Train/test | FP                  | FN                  |
|-----------|---------------------|---------------------|
| 1 90/10   | Correct Beside to fall Sum | Correct — — |
| 1         | Error Side fall left and right 1 | Error — — |
| Correct Beside to fall Sum | Correct — — |
| Error Side fall left and right 2 | Error — — |
| Correct Side fall left and right 1 | Beside to fall |
| 2 80/20   | Correct Beside to fall 1 | Beside to fall |
| Correct Walk to sit Error | Walk to sensor 1 | |
| Correct Side fall Sum | Correct — — |
| Error Forward fall Blackward fall 1 1 2 | Error — — |
| Correct Blackward fall Error | Forward fall |
| Error Forward fall Blackward fall 1 | |
| Correct Side fall left and right Error | Beside to fall 1 |
| Error Forward fall Blackward fall |
| Correct Beside to fall Error | Forward fall 1 |
| Error Forward fall Blackward fall |
| Correct Side fall left and right Error | Walk left to right 1 |
| Error Forward fall Blackward fall 1 |
| 3 70/30   | Correct Walk right to left Error | Walk right to left 1 |
| Correct Walk diagonal left to right Error | Walk diagonal right to left 1 |
| Error Walk diagonal right to left 1 | Walk diagonal right to left 1 |
| Correct Walk diagonal right to left Error | Walk diagonal right to left 1 |
| Error Walk diagonal right to left |
| Correct Walkout sensor Error | Walk to sensor 1 |
| Error Walk to sensor |
| Correct Walk to sit Error | Walk diagonal left to right 1 |
| Error Walk to sit |
| Correct Side fall left and right Error | Forward fall 1 1 2 |
| Error Blackward fall Side fall left and right 2 1 3 |
| Correct Error Forward fall |
| Error Backward fall Side fall left and right 1 1 2 |
| 4 60/40   | Correct Beside to fall Error | Beside to fall 1 2 3 |
| Correct Error Forward fall Side fall left and right 1 2 3 |
| Correct Error Forward fall |
| Error Walk left to right Walk right to left 2 |
| Correct Error Walk right to left |
| Error Walk left to right 2 | Walk left to right 2 |
Analytically, errors decreased when the number of training samples was increased compared with testing samples, and accuracy was considered reliable in the 90:10 training and testing ratio, as shown in Tables 9 and 10. Therefore, the proposed method was proven to be effective for fall classification.

In addition, the fault-positive (FP) and fault-negative (FN) errors shown in the middle column of Tables 6 and 7 were analyzed, and causes of these errors were found, as shown in Table 11. The FP column in Table 10 indicates the number of positive errors in many error patterns, such as misclassifying sitting as falling and misclassifying the type of fall. These errors may cause a caregiver to be alerted to provide help to an elderly person who has fallen. Although these errors were considered a waste of time and energy for the caregivers, they were counted as positive errors and were considered a safety measure. However, the FN column in Table 11 indicates some cases of falling from a chair that were misclassified as sitting on a chair. After analyzing the photographs and signals of this case, as shown by the
examples in Figure 13, respectively, and Figure 14, the video shots and signal patterns that represented falling and sitting looked similar and were hard to differentiate, even when judged by human eyes. This result was considered a limitation of the proposed method. Additional features, such as distance changes measured from the roof, should be considered as future work to solve this limitation. An additional limitation was that an ultrasonic signal was
transmitted from a node as a triangular shape, as observed from the top view. Therefore, small areas between neighboring nodes were regarded as blind areas in which falls were impossible to detect. System designers must carefully design the number of ultrasonic nodes in the array based on the blind zone to be smaller than the minimum human width, as recommended above. This may guarantee protection against not detecting a human fall.

7. Conclusions
To prevent serious risks to elderly individuals after falling in a room, it is necessary to simultaneously monitor elderly behaviors without intruding on their privacy, detect falls, and immediately inform caregivers, when a fall occurs so they can provide urgent assistance. A design method for an ultrasonic sensor-based system is proposed in this study for elderly fall monitoring in a smart room. In this design, ultrasonic sensors are installed as a sensor array on a wall under the condition that the ultrasonic signal covers the area of the whole room with a limited blind zone. The blind zone is determined in advance to be smaller than the width of the human, and the determined blind zone and average human fall duration are used to calculate the distance between neighboring ultrasonic nodes and the total number of ultrasonic nodes on a wall. Then, activated ultrasonic nodes are transmitted in a one-by-one manner without interference in a zigzag scanning line, and the ultrasonic signals, which are time-independent, are classified as a fall or a nonfall by a time-independent-based classifier, such as LSTM. The performance of the proposed method is confirmed to be effective.

Data Availability
Data are available at https://livermutlac-my.sharepoint.com:/f:/g/personal/eleccmk_rmutl_ac_th/EsYB9mvw22PfiJ9zervDc1BSBdMa3enOdK17hf0M2-DA?e=Znch33.

Conflicts of Interest
The authors declare that they have no conflicts of interest.

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