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Local Object Tracking Using Infrared Array for Bed-exit Behavior Recognition

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Bed-exit behavior recognition can be the first line of defense to prevent a subsequent fall and injuries, especially for patients with a high fall risk. The techniques adopted to recognize bed-exit behavior include sensor- and vision-based processing. Generally, vision-based techniques can obtain a wide range of activity information to ensure a good recognition performance. Privacy concerns, however, impede the potential use of vision-based techniques and require the monitoring of activities in only a limited region. This paper focuses on behavior analysis using sensor-based techniques to deal with privacy concerns and other practical issues such as environmental cleaning and behavior differentiation between patients and caregivers. A local object tracking (LOT) technique based on an array of multiple reflective infrared (IR) sensors is developed to monitor user activities in a limited region. The proposed IR-based LOT technique utilizes a finite state machine (FSM) to differentiate the bed-exit activities from a caregiver and in-bed user activities. Furthermore, this bed-exit recognition system is realized as a product prototype to examine its performance in a real ward environment. The experimental results show a correct recognition rate of 99% for 26 bedside activities, four of which are caregiver activities, 16 of which are the everyday activities of the in-bed patient, and six of which are bed-exit activities. In a satisfaction survey conducted at a medical institution, 89% of participants (33 caregivers and 22 patients) considered the system to be effective and 90% of them were satisfied with the quality of the bed-exit recognition prototype.

1. Introduction

Falls are typically a marker related to the health, environment, behavior, and socio-economic status of older people.(1) Findings show that almost one in three community-dwelling people aged over 64 fall every year.(2–4) Fractures, head injuries, and even death are common consequences of falls, and the quality of life for an injured person can be degraded.(5) For those

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with a high fall risk, such as stroke survivors, injured patients, and people suffering from balance disorders, one of the fall prevention approaches focuses on bed-exit behavior monitoring. According to the World Health Organization (WHO) "Global Report on Falls Prevention in Older Age", elderly people living in nursing homes fall more often than those living in the community. Approximately 30–50% of people living in long-term care institutions fall each year, and 40% of them experience recurrent falls.(6) In addition to the community environment, it is essential for nursing institutions to establish an effective bed-exit monitoring system for fall prevention.

Human behavior analysis is a process consisting of activity monitoring and behavior recognition. Generally, there are two types of bed-exit behavior recognition techniques: sensor- and vision-based.(7) In the sensor-based techniques, the behavior recognition system uses fixed modules such as an infrared (IR) sensor,(8–10) a hybrid IR and pressure sensor,(11) a piezoelectric sensor, (12) and radio frequency identification (RFID)(13,14) to detect an object in a limited region. Furthermore, mobile modules based on an accelerometer and gyroscope can be integrated in wearable devices to monitor the movement of an object.(15,16) On the other hand, the vision-based techniques typically employ a deep learning model to recognize human behavior after a data training process. Specifically, the vision source can be a video sequence,(17,18) IR thermal images,(19) or integrated images from an RGB or IR camera.(20,21) Human behavior analysis involves monitoring an object using these techniques to detect objects, and then using the results to recognize bed-exit behavior. Compared with sensor-based techniques, vision-based techniques can obtain activity information in a wider range and have better potential to extract behavior recognition results, such as fall detection after a bed exit.

In addition to being effective, a successful bed-exit system relies on practical considerations at the patient, caregiver, and institution ends. Privacy concerns are the main challenge posed by patients and their families. Obviously, large camera devices deployed in a ward will raise concerns of invasion of privacy. This can impede and even prohibit the use of vision-based bed-exit behavior recognition solutions. In fact, installing a camera in a ward to monitor human activities is feasible only with the agreement of the patient. Another practical consideration arises when the deployment of a bed-exit system can negatively affect the environmental cleaning quality. Problems with system deployment have been observed for both sensor- and vision-based techniques. For vision-based techniques, modification of the ward itself is typically required, while for sensor-based techniques, a sensor fixed in/on the bed may produce an additional burden to caregivers during their service. Any modification of the ward requires a detained plan including ward schedule adjustment and cleaning, and therefore post-installation deployment without ward modification is preferred at the institution end, so that the bed-exit system can be set up and removed as required. Furthermore, activities in a ward environment are diverse and include those of the patient, visitors, and caregivers. Accordingly, a bed-exit system must differentiate bed-exit behaviors from other activities conducted by caregivers.

To address the aforementioned practical issues, we have designed a sensor-based local object tracking (LOT) technique to develop a bed-exit monitoring system. In LOT, the detection range in which specific activities (e.g., bed entry and bed exit) are monitored is limited (e.g., the bedside) and may be limited to part of the patient's body. LOT can ensure that the detection area covering the target is as small as possible to better preserve the privacy requirement. Generally, behavior recognition techniques, especially the vision-based ones, tend to adopt wide-range object tracking to cover as wide detection area as possible so as to obtain more activity information. Although the sensor-based techniques are suitable for LOT applications, the effectiveness of behavior recognition can be determined by the detection range to deal with diverse behaviors in the ward. That is, the detection range decides the trade-off between effectiveness and privacy concerns. In this study, a LOT system based on an array of multiple reflective IR sensors is proposed to balance this trade-off. The IR array is designed to cover only the bed area in a LOT manner, and is combined with a finite state machine (FSM) model to differentiate bed-exit behavior from caregiver activities. Furthermore, the proposed LOT system is realized as a product prototype. This prototype can be fixed to or post-installed at the head of a bed, and achieves a good environmental cleaning quality. In contrast to existing sensor-based techniques,[11–14] in which sensors are placed at different locations of a bed, the structure of the sensor array can be easily integrated into a single device, implying its potential for post-installation deployment. On the other hand, the current IR monitoring systems detect binary bed-related behaviors (i.e., bed exit and bed entry) using a single sensor near the bed.[8–10] Caregiver activities, however, may complicate the bed-related behaviors, having a negative impact on the effectiveness of bed-exit detection. In this study, we adopt the sensor array to continuously track the spatial and temporal variations of user activities in such a way that multiclass behaviors of the patient and caregiver can be detected.

A series of experiments are conducted in a ward environment to monitor 26 predefined bedside activities: six bed-exit activities and 20 non-bed-exit activities associated with the in-bed patient and caregivers. In addition to the experiments, a pilot study involving a questionnaire survey is carried out at a medical institution to collect real-world feedback from 55 participants who experienced the proposed bed-exit prototype. Both experimental and questionnaire results indicate that the proposed LOT-based system is effective in detecting bed-exit behaviors in a ward environment.

This paper is organized as follows. Section 2 describes the proposed LOT system using an IR sensor array for bed-exit detection. Section 3 presents the prototype implementation of the LOT-based bed-exit system, while the experimental and questionnaire results obtained at the medical institution are reported in Sect. 4. Section 5 gives conclusions and future works.

2. LOT Based on Infrared Array

This section describes the concept of LOT and presents a LOT technique using an IR sensor array to recognize bed-exit behavior.

2.1 System overview

Figure 1 illustrates the difference between wide-range tracking and LOT in a smart ward environment. For wide-range object tracking, a tracking device (e.g., video camera) is typically deployed at a higher position than the tracked object so as to capture information over a wide

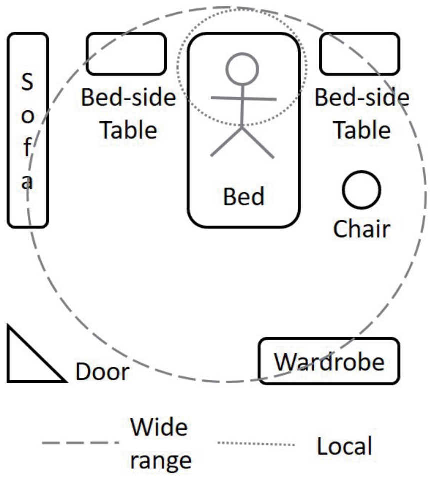

Fig. 1. Wide-range and LOT, where the object is a human body. The region inside the dashed line is the tracking range.

range. This wide-range information can contribute to the tracking of various object behaviors such as bed exit and falling. LOT, however, detects an object using information obtained in a limited range. Compared with wide-range object tracking, LOT is more suitable for single-purpose applications. Although wide-range object tracking is beneficial in designing multipurpose systems, the computational complexity, data transmission bandwidth, and power consumption may be high. In this paper, a LOT technique based on an IR sensor array is proposed to achieve a lightweight and high-efficiency object tracking system.

Figure 2 presents a reference architecture of such a LOT system designed for bed-exit detection. The lower half of Fig. 2 corresponds to the IR array and the upper half shows the essential components used to process the LOT sensing data. In the lower half of Fig. 2, N IR sensors constitute an IR array, in which the distance between two neighboring sensors is d cm. Specifically, an IR reflective sensor, which includes an emitter and a receiver, is selected to detect objects in such a way that the LOT system can be built in a single device. When the IR detection distance is fixed to D, the effective detection area EA of the IR array is given by

$$EA = (N-1) \times d \times D. \tag{1}$$

Within the detection area, the IR array can obtain the object position in accordance with the sensor identity (ID), and the object movement is further analyzed by recording the variation of position with time. The upper half of Fig. 2 corresponds to the LOT system diagram. More specifically, a micro control unit (MCU) is in charge of the sensor data computing, user input (Mic and Buttons), user output (Display and Speaker), and communication. The communication components may include a tip-ring-sleeve (TRS) socket connected to a general call bell system, and a Wi-Fi (officially 802.11)[22] connection with a smart ward system. Both the TRS socket and the Wi-Fi connection aim to either give a notification of a bed-exit event or communicate with

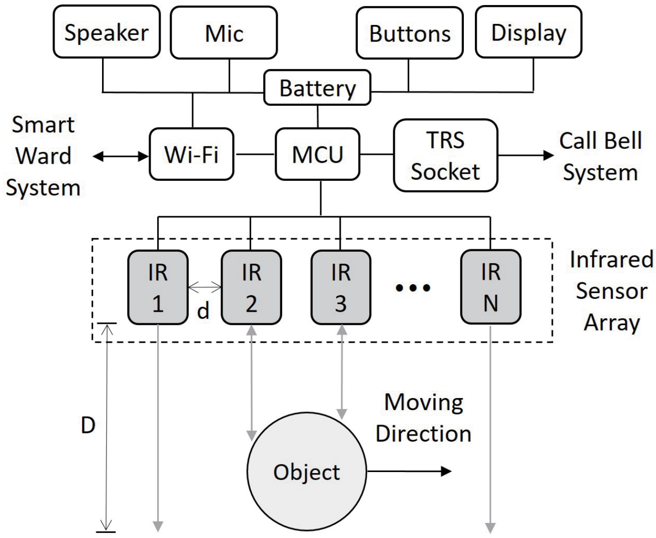

Fig. 2. Architecture of LOT system with sensor array.

the information system, the discussion of which is beyond the scope of this paper, to control the bed-exit system.

2.2 Bed-exit behavior recognition

To detect the object behavior, an FSM can be considered by constructing the states and their corresponding transactions according to the information of the object position and moving direction. As shown in Fig. 3, four main states (i.e., Getup, Bedside, Bed-exit, and In-bed) are included in the bed-exit FSM excluding the Start/Rest state. Let $\boldsymbol{P}$ be the $1 \times N$ position matrix

$$\boldsymbol{P} = \begin{bmatrix} v_0 & v_1 & \dots & v_i & \dots & v_N \end{bmatrix}, \tag{2}$$

where v_i stands for the detection result of the ith IR sensor. v_i is a binary variable in which 0 and 1 represent no object detection and object detection within D by the ith sensor, respectively. Let $\boldsymbol{S}$ be the state matrix with M position matrices:

$$\boldsymbol{S} = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_M \end{bmatrix}. \tag{3}$$

Each row corresponds to a specified N-sensor position in state $\boldsymbol{S}$. For a six-sensor LOT system, the Getup state shown in Fig. 3 may be specified as

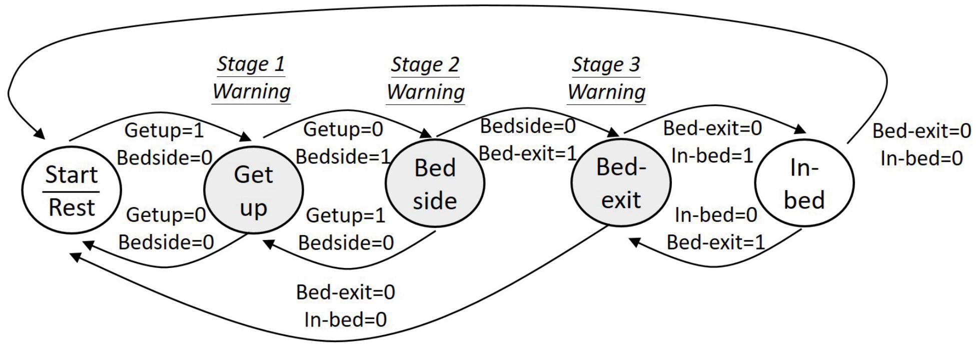

Fig. 3. Bed-exit system states and transactions.

$$\boldsymbol{S}_{\boldsymbol{Getup}} = \begin{bmatrix} 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 \\ 0 & 1 & 1 & 1 & 1 & 0 \end{bmatrix}. \tag{4}$$

In the state matrix [Eq. (4)], four position matrices are included (i.e., $M = 4$) to indicate a human body located in the middle of a bed. In other words, the position matrix may be [1 1 0 0 0 0] or [0 0 0 0 0 1] when the target is located at the side of the bed.

At time t, the LOT system detects the object position $\boldsymbol{P_t}$ and examines whether $\boldsymbol{P_t}$ is in state $\boldsymbol{S}$ by first calculating the residence matrix

$$\boldsymbol{R} = \boldsymbol{P}_t \times \boldsymbol{S}^T, \tag{5}$$

where $\boldsymbol{S^T}$ is the transpose of state matrix $\boldsymbol{S}$. The residence threshold is denoted as $\boldsymbol{H}$ ($\boldsymbol{H} \geq 0$), and $\boldsymbol{P_t}$ can be determined to be in state $\boldsymbol{S}$ when the value of any element in $\boldsymbol{R}$ is greater than or equal to $\boldsymbol{H}$. Consequently, the residence matrix [Eq. (5)] combined with the residence threshold defines a transaction condition in the FSM. To differentiate the bed-exit behavior from other behaviors, three transaction conditions based on residence thresholds (i.e., H_1, H_2, and H_3) are associated with each state. The non-bed-exit behaviors include caregiving activities and in-bed activities such as turning over and hand waving. The first transaction condition corresponds to the object position in the bed, whereas the second transaction condition examines whether the target or another object (e.g., caregiver) is located within the detection area. In Eq. (4), the position matrix for the Getup state implies that the object is in the middle of the detection area. Accordingly, the state matrix can be simplified to [0 0 1 1 0 0], and the corresponding residence threshold H_1 is set to 2. On the other hand, the position matrix specified for the boundary examination is given by [1 0 0 0 0 1], and the required residence threshold H_2 is 0. In the Getup state, the two transaction conditions are $H_1 = 2$ and $H_2 = 0$. These conditions indicate that the object is in the middle of the bed. Furthermore, Eq. (4) can be rewritten as

$$\boldsymbol{S}_{\boldsymbol{Getup}} = \begin{bmatrix} 001100 \\ 100001 \end{bmatrix}. \tag{6}$$

On the basis of the state matrix [Eq. (6)], an object position $\boldsymbol{P_t}$ = [0 1 1 1 0 0] detected by the six-sensor LOT system can obtain $\boldsymbol{R}$ = [2 0]. Consequently, the position $\boldsymbol{P_t}$ remains in the Getup state when the resultant values of the residence matrices satisfy the transaction conditions mentioned above:

$$\boldsymbol{R_t} = \begin{bmatrix} 011100 \end{bmatrix} \times \begin{bmatrix} 001100 \\ 100001 \end{bmatrix}^T = \begin{bmatrix} 2 = H_1 \\ 0 = H_0 \end{bmatrix}. \tag{7}$$

For another object position $\boldsymbol{P_{t+1}}$ = [1 1 0 0 0 0], its corresponding residence matrix is computed as follows:

$$\boldsymbol{R}_{t+1} = \begin{bmatrix} 110000 \end{bmatrix} \times \begin{bmatrix} 001100 \\ 100001 \end{bmatrix}^T = \begin{bmatrix} 0 \neq H_1 \\ 1 \neq H_0 \end{bmatrix}. \tag{8}$$

Then, $\boldsymbol{P_{t+1}}$ is not in the Getup state according to the transaction conditions.

The first two transaction conditions are related to the object position and can be effective for detecting whether the object is on the bed or at the edge of the bed. The caregiver activities can therefore be recognized from the fact that most caregiver activities are conducted at the edge of the bed. The hand-related activities such as hand waving and fetching, however, are easily confused with the activities defined in the FSM states. For instance, the position matrices for fetching are similar to those of the Getup state. Accordingly, a third transaction condition with residence threshold H_3 is used to filter hand-related activities when the object is on the bed. More specifically, the transaction condition H_3 = 1 holds when the incoming position is maintained for n seconds ($n \geq 0$). This condition is based on the observation that most hand movements have a higher speed than body movements. We denote the state transaction as a binary variable $\widehat{ST}$ expressed as

$$\widehat{ST} = \begin{cases} 1, & \text{if all three transaction conditions are met,} \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

As shown in Fig. 3, the currently active state computes Eqs. (5) and (9) in order for a new $\boldsymbol{P_t}$ to obtain the state transaction variable at time t. The binary transaction variable for the Getup state is *Getup*, the variable for the Bedside state is *Bedside*, and so forth. When a new $\boldsymbol{P_t}$ does not remain in the current state (i.e., its binary transaction variable is 0), Eq. (9) is calculated for other neighboring states to determine the state transaction.

In the proposed bed-exit FSM for the six-sensor LOT system (Fig. 3), a bed-exit behavior is regarded as a series of ordered state transactions. That is, a bed-exit behavior starts from the Getup state, then the object turns around to the bedside, and finally the object leaves the bed. After the bed-exit event, either the object returns to the bed (i.e., In-bed state) or this Bed-exit state remains unchanged. In the latter case, the state returns to the initial Start state and ignores any potential activities until a new Getup state is detected. This is because under the situation that no object is detected on the bed, all subsequent activities are unrelated to the bed-exit behavior, for instance, caregiving activities and even the activity that the object returns to the bed. The proposed FSM also defines three warning stages when the object is detected in the following states: Getup, Bedside, and Bed-exit. In addition to the stage-3 warning, which is essential for bed-exit detection systems, stage-1 and stage-2 warnings can be employed for users with high fall risks. When the current state is in the warning stage, the system must notify caregivers and/or the care institution. In this study, the proposed LOT prototype utilizes multiple notifications including a voice, call bell, and messages via Wi-Fi connection. Details of the prototype implementation are given in Sect. 3.

2.3 FSM parameter selection

This subsection presents the state matrices and transaction conditions for the main states in the FSM. The FSM parameters are listed in Table 1. The first two transaction conditions are used to examine the object position, and therefore need to be combined with the state position matrices. More specifically, the position matrices combined with the first transaction condition are considered in the object position examination. In the Getup state, the object position is assumed to be in the middle of the bed. When the object gradually moves to leave the bed, "1"s occur on one of the two sides of the matrix. Note that the object can move in two different directions (i.e., right and left), and two position matrices are defined accordingly. When the object moves to the right side of the bed, the position matrix [0 1 1 0 0 0] in the Bedside state changes to [1 1 0 0 0 0] in the Bed-exit state. Alternatively, the position matrix [0 0 0 1 1 0] in the Bedside state changes to [0 0 0 0 1 1] in the Bed-exit state. In the In-bed state, the position matrix [0 1 1 1 1 0] combined with the transaction condition $H_1 \geq 2$ indicates that the object is on the bed but not at the edge of the bed.

The position matrices combined with the second transaction condition are considered in the edge examination. This transaction condition aims to clarify whether any caregiving activities

Table 1
FSM parameters for LOT system with six IR sensors.

State	Getup	Bedside	Bed-exit	In-bed
Position matrices (H_1/H_2)	001 100 ($H_1 = 2$)	{011 000, 000 110} ($H_1 = 2$)	{000 011, 110 000} ($H_1 \geq 1$)	011 110 ($H_1 \geq 2$)
	100 001 ($H_2 = 0$)	100 001 ($H_2 = 0$)	100 001 ($H_2 = 1$)	100 001 ($H_2 = 0$)
H_3	$H_3 = 1$	$H_3 = 1$	$H_3 = 0$	$H_3 = 1$

occur even when the object is detected on the bed. When a caregiver stands on the right/left side of the bed to conduct care services, bed-exit behavior detection and possible warnings are unnecessary. For all four states in the FSM, the position matrix associated with this second transaction condition is fixed to [1 0 0 0 0 1]. In the Bed-exit state, the second transaction condition for the object at the edge of the bed is $H_2 = 1$, whereas $H_2 = 0$ for the other three states.

The position matrices combined with the third transaction condition are considered in the time examination. On the basis of this condition, the IR-based LOT system can avoid regarding the hand movement as body movement, which is utilized to recognize the bed-exit behavior by default. For the Getup, Bedside, and In-bed states, the third transaction condition is $H_3 = 1$, and therefore the first two transaction conditions must be continuously satisfied for a prespecified time slot. In the Bed-exit state, however, the third transaction condition is set to $H_3 = 0$. This is because when the FSM changes from the Getup or Bedside state to the Bed-exit state, the bed-exit behavior can be confirmed and an immediate warning or notification should be given.

3. System Implementation

The aim of this study is to realize a LOT system with an N-sensor array for a bed-exit monitoring application. Figure 2 in Sect. 2.1 illustrates the architecture for the bed-exit system under consideration. To further examine the effectiveness of the LOT-based bed-exit system, the architecture of the N-sensor LOT system presented in Fig. 2 is implemented as a product prototype. The prototype implementation includes the hardware and firmware design. Figure 4 presents the hardware component assembly. As shown in Fig. 4(a), the outer case consists of a metal backplane, plastic shell, and buttons for the user input. The rectangular hole in the front view of the shell is reserved for the LCD display, while the multiple circular holes in the backplane are used for screws to fix the LOT system either on a wall or a mobile stand. Figure 4(b) shows the main components required to build the system. In Fig. 4(b), the MCU and TRS modules are attached on a printed circuit board (PCB), and then the other components, including the IR sensors, display, microphone, speaker, and battery, are connected to the PCB with wires. A battery is adopted as an additional source to supply power in the case of a short-term power failure. Figure 4(c) gives a snapshot of the system prototype after component assembly. As shown in Fig. 4(c), the current prototype utilizes six reflective IR sensors, which are deployed on both sides evenly. Furthermore, the outermost sensor is further from its neighboring sensor so as to detect the bedside position more effectively. Figure 4(d) presents a front view of the prototype. With the IR array with six sensors, the prototype can detect the position and moving direction of the object, from which it recognizes the bed-exit behavior.

In the firmware design, the FSM diagram defined in Fig. 3 is realized and operates in the MCU. When the FSM state is in the warning stage, a signal is sent via the TRS to enable the alarm in the call bell system; meanwhile, a prespecified message can be transmitted via the Wi-Fi module. Additionally, the firmware reads the user request from the buttons and shows the corresponding text in the display module to respond to the request. User requests include the adjustment of the time and date, voice recording, and adjustment of the voice volume. In our implementation shown in Fig. 4, the voice processing is carried out using a voice/speech chip on

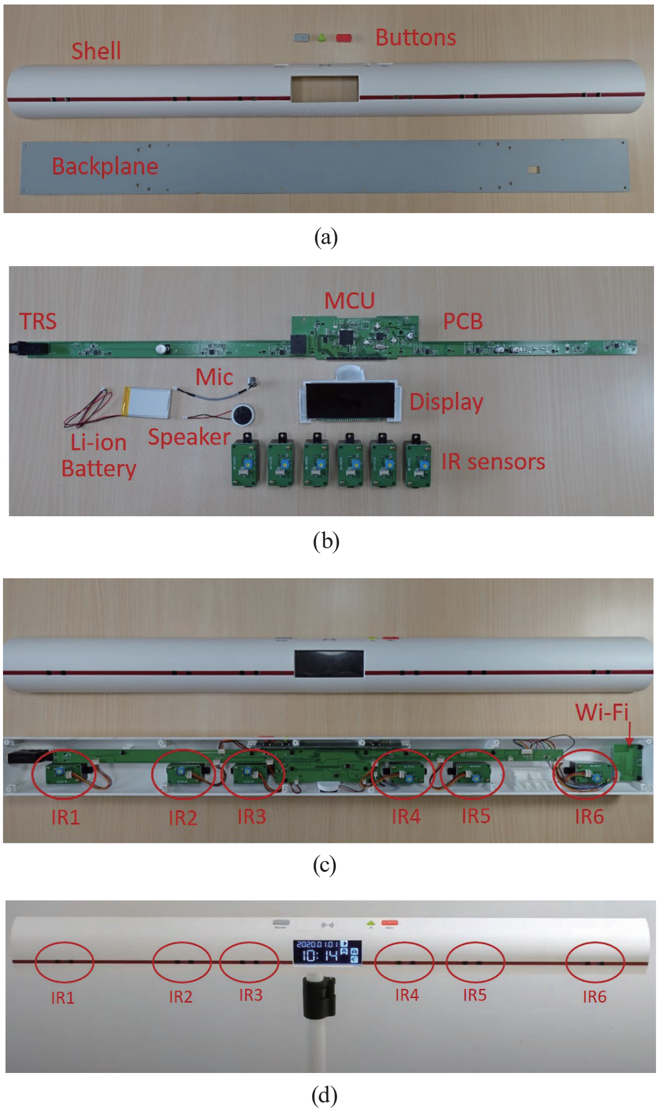

Fig. 4. (Color online) Prototype of bed-exit system: (a) components of outer case; (b) circuit components; (c) interior view after assembly; and (d) front view of prototype.

the PCB. Accordingly, the prototype supports a local warning to notify a caregiver near the bed in the presence of a bed-exit event.

4. Performance Results and Analysis

This section presents the performance of the LOT-based bed-exit system in terms of experimental and questionnaire results. Both results are obtained using the prototype shown in Fig. 4. Specifically, the bed-exit prototype is deployed at the head of the bed in such a way that the detection range of the IR array can cover the bed. The IR detection distance is set to 1.6 m, which is slightly shorter than the length of the bed (typically 2 m) to avoid the interference of non-bed-exit activities at the bed end such as cleaning and caregivers walking by.

4.1 Experiments

Our experiments were conducted in a ward environment and involved 26 bed-related activities, each of which was repeated 240 times. The 26 activities can be divided into three classes: bed exit, in bed, and caregiving. The first two classes focus on the activities of the patient, while the third class corresponds to the activities of the caregiver.

Table 2 lists the experimental results of six bed-exit activities. In the experiment, a complete bed-exit activity indicates that a user enters the bed from one side and exits from the same or the other side. Figure 5 shows a sequence of snapshots for the bed-exit scenario of right enter, left exit. In the bottom three snapshots from right to left, the female subject leaves the bed in accordance with the state transactions (i.e., Getup, Bedside, and Bed-exit) in the FSM described in Sect. 2.2. In Fig. 5, it can be clearly seen that the proposed prototype is attached to a mobile stand and can be set at the head of the bed in a post-installation manner accordingly. Since the aim of this study is to observe the bed-exit behavior, the correct rate is used to evaluate the successful detection of bed exit. On the other hand, the detection of bed entry as a bed-exit event is recorded as a detection error. As shown in Table 2, an average correct rate of more than 99% was observed for the six bed-exit activities. Among the bed-exit activities, the "roll right to exit bed" activity has a slightly lower correct recognition rate than the others. Inspecting the state transactions for the failed "roll right to exit bed" activities suggested that the IR array may not capture the body rolling movement. Figure 6 presents a sequence of snapshots of this "roll right

Table 2
Statistical results of six bed-exit activities.

Activity (Bed exit)	Corr. rate (%)	Err. rate (%)
Left enter, left exit	100 (exit)	0 (enter)
Left enter, left exit	100 (exit)	0 (enter)
Left enter, right exit	100 (exit)	0 (enter)
Right enter, left exit	100 (exit)	0 (enter)
Roll left to exit bed	100	—
Roll right to exit bed	99.17	—

Fig. 5. (Color online) Bed-exit activity: right enter, left exit. Images are arranged in clockwise order from top left.

Fig. 6. (Color online) Bed-exit activity: roll right to exit bed. Images are arranged from left to right.

to exit bed" activity. In the second snapshot from the left, the subject rolls her body to get up from the bed, and then the bed-exit prototype omits the Getup state and jumps to the Bedside state. Consequently, the bed-exit detection fails. To reduce detection failure for rolling activities, we suggest the deployment of the bed-exit prototype lower than the shoulder of the subject. On the other hand, the bed-exit prototype should be higher than the nose of the subject lying down on the bed.

Table 3 presents the results of non-bed-exit activities including four caregiver activities and 20 everyday body activities. Figure 7 shows the snapshots of the caregiver activity "help out of bed" from the right side. In Fig. 7, the caregiver stands on the right side of the bed during the entire activity, and the caregiver's behavior can be filtered out by the second transaction condition defined in Table 1 for the Getup and Bedside states (i.e., position matrix [1 0 0 0 0 1] with H_2 = 0). The second transaction condition ensures that the bed-exit event is that of the subject itself, and ignores the activities associated with caregiving. Additionally, the activities "left in, left out" and "right in, right out" indicate that the caregiver walks to near the bed and then walks away after finishing the caregiving service. From Table 3, it can be seen that (1) the caregiver activities have a 0% detection error rate, and (2) most body activities are successfully detected as non-bed-exit behavior, except for a few right/left-hand fetch events from the belly. Figure 8 shows a sequence of snapshots of a right-hand fetch activity. By inspecting the hand fetch event, it was found that the slower hand movement of reaching out might be regarded as a body movement associated with leaving the bed (see the middle two images in Fig. 8), and the resultant detection error rate is 0.83%.

4.2 Clinical survey

To further examine the effectiveness of the LOT-based bed-exit system, the prototype bed-exit monitor presented in Fig. 4 is deployed at Changhua Christian Hospital, Taiwan. In this pilot study, a total of 55 volunteers (22 patients and 33 caregivers) complete a questionnaire survey after experiencing the proposed bed-exit system.

As shown in Fig. 9(a), 89% of participants consider the LOT-based bed-exit system to be effective, while only 6% indicate that this bed-exit system does not meet their expectations. On the other hand, Fig. 9(b) shows the reviews of caregivers for the proposed prototype. 89% of the caregivers involved in the study agree that the LOT-based bed-exit system can reduce their

Table 3
Statistical results of 20 non-bed-exit activities: four cases are for caregiver and 16 cases are body activities.

Category	Activity	Err. rate (%)	Category	Activity	Err. rate (%)
Caregiver	Help out of bed (left side)	0	Body	Right-side left-hand fetch (chest)	0
	Help out of bed (right side)	0		Right-side right-hand fetch (chest)	0
	Left in, left out	0		Left-side right-hand fetch (chest)	0
	Right in, right out	0		Get up, left-side left-hand fetch	0
Body	Raise right hand	0		Get up, right-side right-hand fetch	0
	Raise left hand	0		Wave left	0
	Pull quilt	0		Wave right	0
	Left-side left-hand fetch (belly)	0.83		Waving both hands	0
	Right-side right-hand fetch (belly)	0.83		Turn over	0
	Left-side left-hand fetch (chest)	0		Get up and lie down	0

Fig. 7. (Color online) Caregiver activity: help out of bed (right side). Images are arranged from left to right.

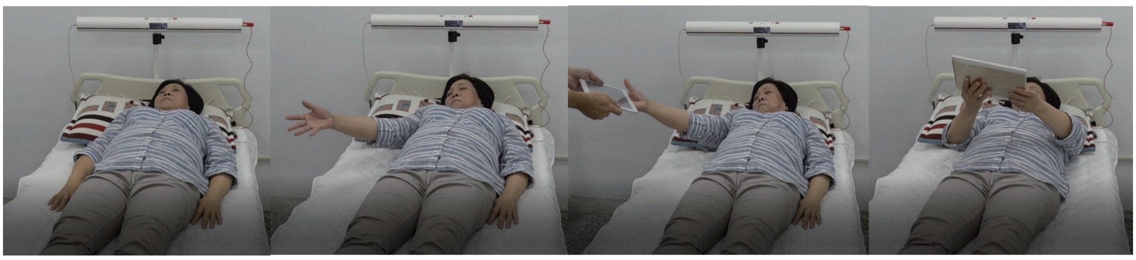

Fig. 8. (Color online) In-bed activity: right-side right-hand fetch (belly). Images are arranged from left to right.

burden in caring for patients with high fall risks, and only 3% of them indicate that the operation of such a bed-exit monitor might become an additional burden in practice. This implies that it is essential to design a good user interface for the commercialization of the prototype. From Fig. 9(c), 90% of participants agree that the prototype quality is good, with 10% of them giving a neutral response. This result can be useful in improving the prototype implementation. Finally, 87% of participants are satisfied with the innovation of the LOT-based bed-exit system [Fig. 9(d)]. To conclude, most participants agree that the proposed LOT prototype has a good design and satisfactorily detects bed-exit behavior.

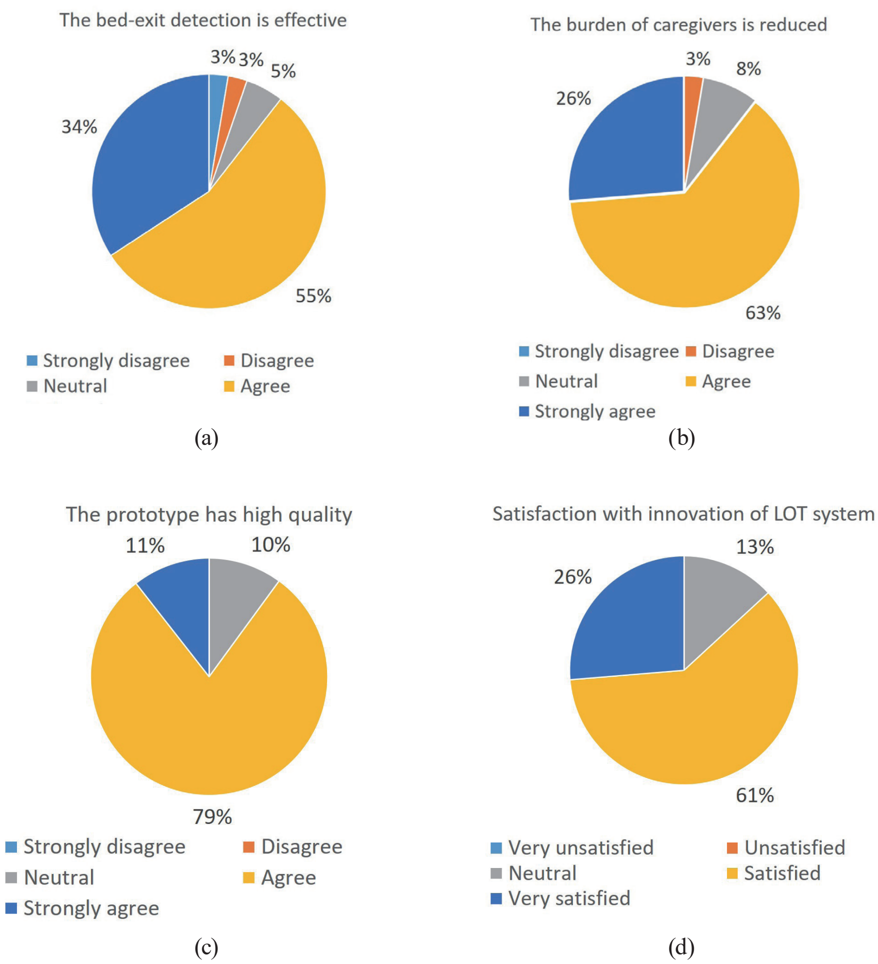

Fig. 9. (Color online) Questionnaire results: (a) effectiveness of LOT system; (b) burden reduction of caregivers; (c) prototype quality; (d) innovation of LOT system.

5. Conclusions

We studied LOT to detect human behavior in a limited region and presented a LOT-based system using an IR sensor array to detect bed-exit behaviors. Specifically, the IR sensor array comprises multiple reflective IR sensors to track spatial and temporal user activities in a continuous manner. Compared with wide-range object tracking, the LOT system can be more adaptable to privacy requirements and post-installation deployment. To provide reliable bed-exit behavior recognition, an FSM model is proposed with an IR array of six reflective sensors. In the proposed FSM model, the bedside condition is essential in detecting the caregiver activity. The time-based examination in FSM can also be effective for differentiating body activities from bed-exit activities. Consequently, a bed-exit event is detected via continuous FSM state transactions without interference due to caregiver and body activities.

The proposed system was implemented as a product prototype and its performance was evaluated in a realistic ward environment. The user activities under consideration consisted of six bed-exit activities, four caregiver activities, and 16 everyday body activities. The experimental results show that this LOT-based system can achieve a correct bed-exit detection rate of more than 99%, and a questionnaire study indicated that 89% of participants who experienced the prototype consider it to be effective in preventing fall events. Future tasks include reducing the detection error rate using a multidimensional sensor array and adding more activities in the experiments.

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