Hindawi
Applied Computational Intelligence and Soft Computing
Volume 2018, Article ID 5434897, 15 pages
https://doi.org/10.1155/2018/5434897

Research Article

Post-Fall Intelligence Supporting Fall Severity Diagnosis Using Kinect Sensor

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Received 20 October 2017; Revised 26 January 2018; Accepted 12 March 2018; Published 3 June 2018

Academic Editor: Xiaohui Yuan

This paper proposes a fall severity analytic and post-fall intelligence system with three interdependent modules. Module I is the analysis of fall severity based on factors extracted in the phases of during and after fall which include innovative measures of the sequence of body impact, level of impact, and duration of motionlessness. Module II is a timely autonomic notification to relevant persons with context-dependent fall severity alert via electronic communication channels (e.g., smartphone, tablet, or smart TV set). Lastly, Module III is the diagnostic support for caregivers and doctors to have information for making a well-informed decision of first aid or postcure with the chronologically traceable intelligence of information and knowledge found in Modules I and II. The system shall be beneficial to caregivers or doctors, in giving first aid/diagnosis/treatment to the subject, especially, in cases where the subject has lost consciousness and is unable to respond.

1. Introduction

Falls are a major cause of fatal injury, especially for elderly people. Falls for elderly persons can adversely affect their health status and quality of life. They may be a cause of morbidity and mortality, particularly for those who are suffering from dementia or Alzheimer's disease because they are stricken with forgetfulness, confusion, impaired decision-making ability, and delayed responses when asking for assistance [1]. This is still true at present, even though there exists a revolution of automatic fall detection systems based on various approaches, for example, acoustic and ambient sensor-based, kinematic sensor-based, and computer vision and Natural User Interface (NUI) sensor-based approaches [2]. A common limitation of them is no provision of timely and traceable incident information to physicians for making fall diagnosis which could lead to proper treatment and even to support first aid which is given by caregivers. Such a limitation becomes serious if the subject lives alone and is unable to respond or is conscious but cannot recall the incident details. Lately, Patsadu [3] and Patsadu et al. [4] proposed fall motion detection with fall severity level estimation based on velocity and kinetic energy as a surrogate for seriousness of injury on three areas of the body: head, hip, and knee. However, this work also has a limitation because the fall severity alone is not enough to support diagnosis by physicians for further treatment.

In response to this challenge, this paper proposes an intelligent system that encompasses the framework of fall detection in our previous work [3, 4] so that ongoing diagnosis for severity of fall impact on important organs can be systematically supported for immediate first aid or further treatment. Three main parts of post-fall intelligence are proposed to ensure threefold contributions: (1) insightful and reliable analytic information about fall sequence and level of impact on important body joints based on the monitored data gathered via the discreet Kinect; (2) ability to accurately make a prompt notification of a fall to the persons in charge by a supportive and manageable dashboard; (3) ability to perform an online analytical process on the chronological data of a fall to support diagnosis in the later-treatment stage.

The first part of the proposed system is the selection of appropriate fall severity factors as proposed by a domain expert, a physician of medicine in rehabilitation. These

factors include derived expert opinion rules of sequence of body-joint fall on impact, velocity on impact, kinetic energy on impact, and duration of any motionless state after a fall. The second part is notification sent after a fall to convey incident details via electronic communication channels such as a smartphone, tablet, or smart TV set. Notification is a crucial early step to take in response to a fall. So, the system can notify and help reduce injury even though the caregiver or relevant persons are not with the elderly during or after a fall. The last part is the provided information of fall severity determination by the persons in charge (e.g., caregivers and physicians). This insightful information helps the personnel to give proper assistance and diagnosis intelligence for prescribing treatments based on injury severity of the three selected risk areas of the body: head, hip, and knee. These three parts are crucial for successful processing of post-fall intelligence in any smart home system.

The organization of this paper is as follows: Section 2 presents related works; Section 3 describes the methodology of our proposed system; Section 4 shows the experimental results and discussions; Section 5 presents the demonstration; finally, a conclusion and future work directions are presented in Section 6.

2. Related Works

Intelligent systems have been developed to collect and analyze data based on experience, security, and connectivity for decision-makers [5]. For the domain of healthcare, there are various intelligent systems such as medical diagnosis, robot control, remote sensing, and real-time monitoring.

In the case of falling with the elderly, there are many attempts to provide protection against falls and send timely information to relevant persons to help get a fallen elder out of danger in time. According to the fall detection techniques used, there are several areas of research for fall detection and notification systems using Kinect. K. C. Lee and Y. V. Lee [6] and Mundher and Zhong [7] have created a fall detection system with message notification that uses a cell phone to send a Short Message Service (SMS) message to the caregiver. Kawatsu et al. [8] also proposed a fall detection system which resembles the one of Mundher and Zhong [7]. When a fall has occurred, the system sends a warning message via email and Multimedia Messaging Service (MMS). Moreover, Rantz et al. [9] proposed real-time alerts of actual falls that are sent to clinicians or caregivers via mobile devices. Pathak and Bhosale [10] presented a method for fall detection based on body-joint positions of human subjects. After a fall detection is encountered, an alert is sent to caregiver by using a SIM900A GSM modem. In addition, Stone and Skubic [11] proposed a method for a real-time fall alert with embedded depth video clip based on hyperlink. When a fall occurs, notification is sent to facility staff members via email.

Once a fall event is detected, Gagana and Vani [12] proposed that a serious fall and consequent injury may lead to the risk of death and "post-fall syndrome." Fenton [13] reported that body-joint falls impact not only vary but also result in different levels of severity. Therefore, the system needs to analyze body-joint positions being impacted based on fatal impact. This work proposed a method for fall detection by analyzing tracked key body joints of subject using a depth-camera. There are several researches to detect body joints position in the human body using a Kinect based on depth image [14, 15]. Amongst important body positions, head position was reported as the first one that could suffer the most impact. Head position is also a suitable monitored position to resolve occlusion problem in fall detection as reported in the work of Bian et al. [16]. In addition, elderly persons over the age of 70 have a high risk of traumatic brain injury-related hospitalization and death due to falls [17]. The causes of traumatic brain injury come from prolonged unconsciousness, as well as the severity of symptoms. Unfortunately, elderly persons have the most risk of hip fractures because they frequently use hip hit on the floor, although they have a low speed during the fall [18]. The third rank of injury from falls is knee bone fracture [19]. Finally, a fall may result in hand bone fractures [20].

Generally, the severity of injury can be evaluated based on key influencing factors, for example, the height of the fall, post-fall velocity, or acceleration of the impacted position and kinetic energy of the fall [4, 21–23].

To our knowledge, the integrated post-fall intelligent system has never been explicitly defined to provide the probable post-fall intelligence of accidental falls that may happen during daily routines. Such an information system would be valuable not only for first aid but also for supporting decisions about subsequent care. Unfortunately, most of the existing models have been designed for medical healthcare staff members based on paper form per incident to inquire about fall information (i.e., fall history, activity of daily life, congenital diseases, and side-effects of medicine) from patients or caregivers [24–27].

It is essential for the model of post-fall intelligence to take into account the integrated fall history and crucial information using online information without the intention to replace the specialist's judgment that both warns and supports caregivers to take actions on first aid or assists specialists in deciding on subsequent care.

Next, we discuss in detail the design methodology for systematically determining post-fall intelligence.

3. Proposed System

The proposed *post-fall intelligence* aims at providing timely information to support immediate decisions of caregivers who give first aid to a fallen person or providing traceable chronological information to physicians for later diagnosis or treatment. Figure 1 shows the architectural design of our proposed system integrated with the fall detection system as proposed in Patsadu et al. [4]. When setting up an experiment, we used a Kinect to track the motion of a human in an indoor environment. The Kinect was set up approximately 1 meter above the floor to cover a room which has dimensions of approximately 5×7 m. (see Figure 2). Kinect generated a video stream of 15 body-joint positions (X, Y, Z) with a resolution of 640×480 at a rate of 30 frames

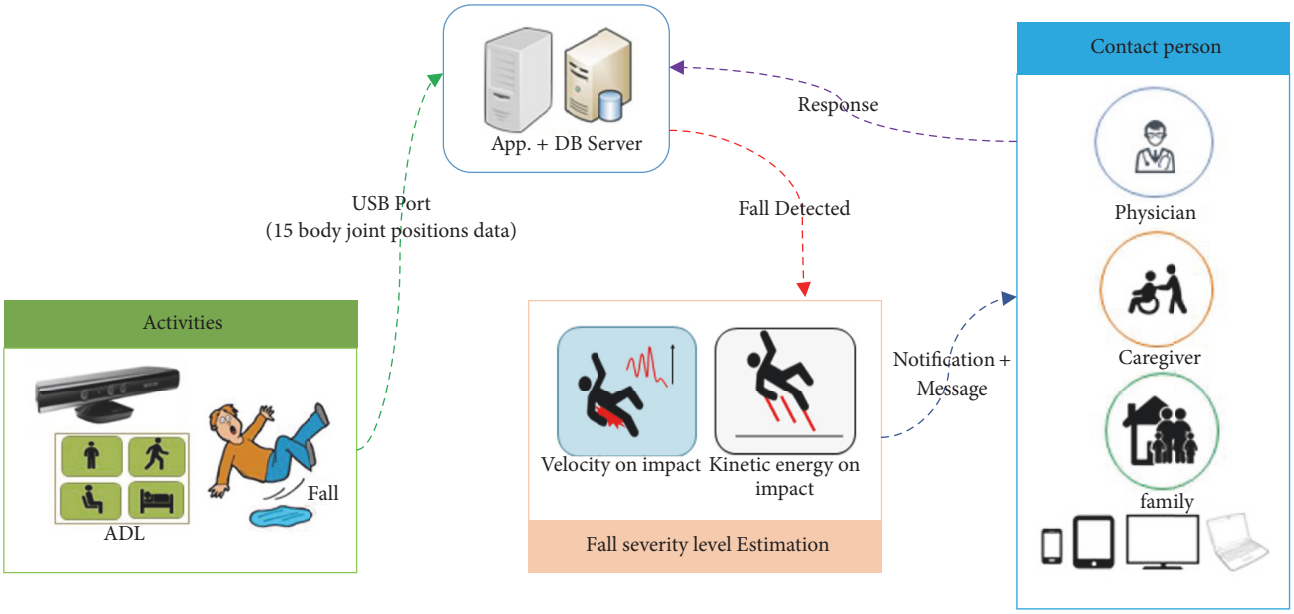
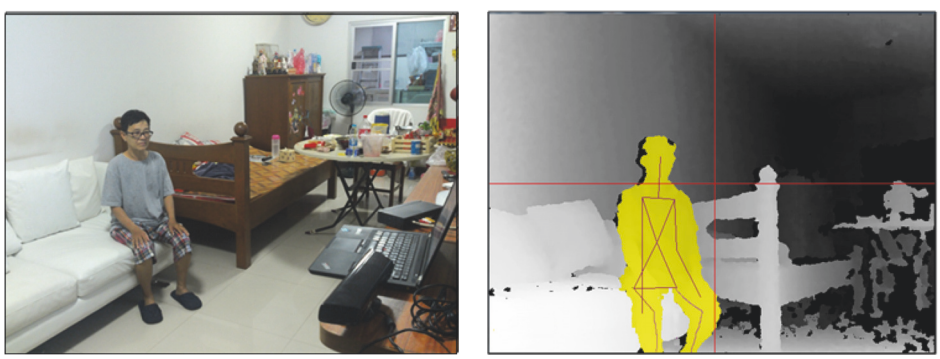


Figure 1: Architecture of proposed system.



(a) RGB of monitoring of a subject (b) Depth image of monitoring of a subject

Figure 2: Setting for proposed system within a home.

per second (fps) which was extracted using the OpenNI depth metadata process [28]. The severity analytic and post-fall intelligence works hand-in-hand with the fall detection system. When a fall occurs, the data from the fall detection system will be instantly delivered to the intelligence server for analyzing incident information (e.g., expert opinion rules of body-joint fall impact, velocity on impact, kinetic energy on impact, duration of motionless state after a fall, and a fall video clip recorded during a fall). In a few seconds, a notification message packed with the mentioned analytic data will be sent to assigned relevant persons (e.g., caregivers, family, and physicians) via a set of assignable communication channels such as a smartphone, tablet, or smart TV set. Once the message is received, the responsible persons can click a button on the notification dashboard to take charge.

3.1. Integrated System of Fall Severity Analytic and Post-Fall Intelligence. Once a fall is detected using the algorithm of our previous work [4], *the post-fall intelligence* to support fall severity diagnosis on three key body joints, head, hip, and knee, will be proceeded. The process of *post-fall intelligence* is comprised of three main steps, namely, the analysis of fall severity factors, notification, and fall severity determination.

3.1.1. Investigating Fall Severity Factors to Support Fall Severity Diagnosis. The severity factors in this research are coinvented by a domain expert in rehabilitative medicine to ensure the pragmatically effective support of fall severity diagnosis. The four fall severity factors are defined as the expert opinion rules of body-joint fall impact, duration of motionless state after a fall, velocity on impact, and kinetic energy on impact. The detail is presented next.

(1) Expert Opinion Rules of Body-Joint Fall Impact. This factor analyzes body-joint positions being impacted to examine the characteristics of a fall and any consequent injury. Normally,

Table 1: Rules for examination of prolonged duration of motionlessness.

Rules	First position (hit floor)	Duration that subjects remained motionlessness	Output
1	head 	>30 seconds	Prolonged motionlessness/did not receive assistance
2	hip or knee 	>5 minutes	

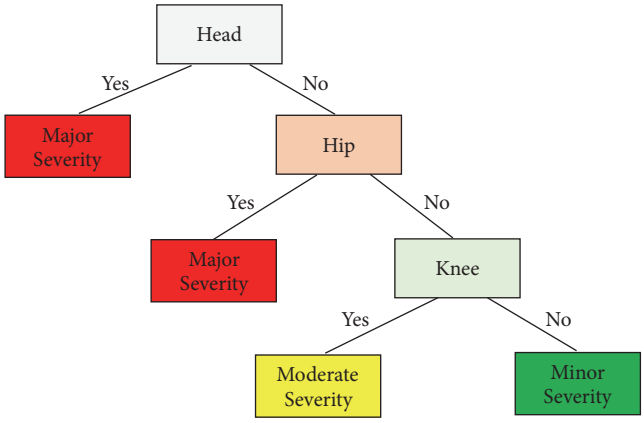


Figure 3: Body-joint fall impact divided into severity level.

certain body-joint position fractures can frequently occur when falling, especially, the hips, knees, hands, and so on [29]. Fractures, especially hip fractures, can cause a disability and have a high mortality rate. Head trauma is also frequently found. The most dangerous events occur when the head or hip is the first body part that impacts the floor or obtrusive objects. Empirically, the rule of considered body-joint positions being impacted was agreed by a domain expert in rehabilitation medicine as shown in Figure 3. The proposed rule is divided into two stages: examination of the body-joint position that firsts hit the floor and examination of consequent severity level. The stages are shown as follows.

(1) The first stage considers the body-joint position that first hits the floor and the velocity of the movement to identify the threshold value and studied the patterns of the velocity of the movement of each body part in a huge amount of fall data. The threshold value was trained using 1,320 fall video clips of eight subjects randomly selected from a total of 1,650 fall video clips as described in our previous work [4]. Each subject performed a simulated fall with different types of actions and different speeds. The result shows that the suitable threshold value is equal to 0.03 m/s. So, if the velocity of the considered body-joint position is less than or equal to the indicated threshold, that body-joint position is hitting the floor for the time being.

(2) The second stage is to identify the severity level acquired in the first stage. The severity level is considered from the body-joint positions being impacted. In the medical expert's opinion, the head or hip position is most impacted after a fall. For the knee position and hand, the severity level is moderate or minor impact, respectively.

Additionally, more than one body-joint position has the possibility of hitting the floor. Therefore, the system will also report the ordering sequence of the body-joint positions impacted, for instance, "knee → hand → head", "hip → hand → head", or else.

(2) Duration of Motionless State after a Fall. This post-fall factor is used to examine any subsequent prolonged motionless status after a fall which may lead to hypothermia, dehydration, or bronchopneumonia [30]. The post-fall phase is defined as the duration that starts when a fall is detected. Figures 4(a)–4(d) conceptualize three phases of fall and the probability of fast recovery or prolonged motionless in the 3rd phase of post-fall. This suggests two subphases to be considered: the recovery phase and the motionless phase. For the recovery phase, the subject is able to recover within a few seconds due to minor injury (see Figure 4(b)). For the motionless phase, the subject may be unable to get up again without assistance due to severe injury or unconsciousness (see Figures 4(c)-4(d)).

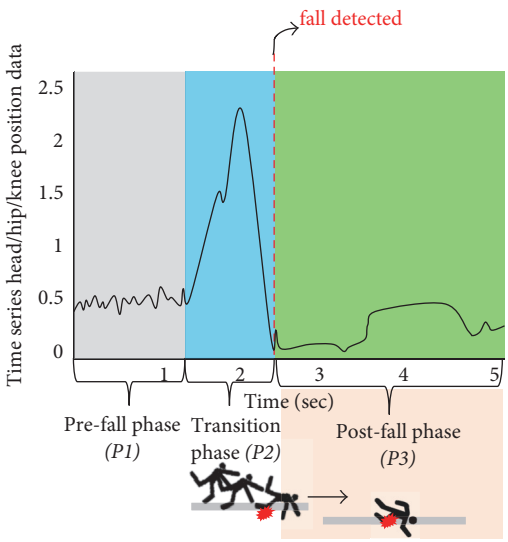
The process to detect the duration of having prolonged motionlessness can be divided into three stages as follows.

(1) Examination of the body-joint position that first hits the floor is conducted by using the body-joint fall impact algorithm as described in Section 3.1.1(1).

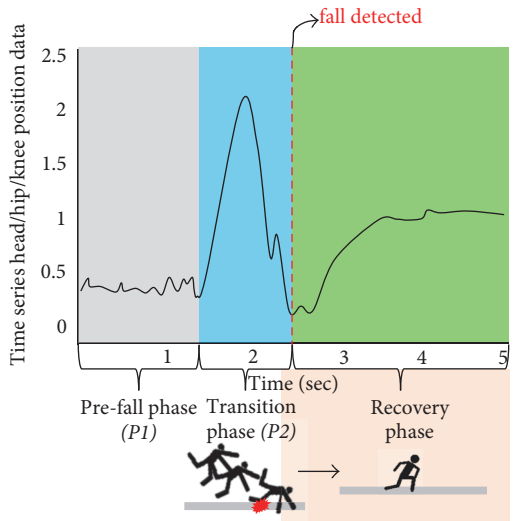
(2) Examination of duration of subject's motionlessness: to identify the threshold value, the patterns of the velocity of the movement of each body part were studied in a huge amount of fall data. The data set was trained similar to what is shown in Section 3.1.1(1). Empirically, the suitable threshold value is equal to 0.08 m/s. Indeed, if the velocity of the movement of each body part is less than or equal to the indicated threshold, it means that the subjects remained motionless or did not receive assistance.

(3) Examination of prolonged duration of motionlessness is based on the medical expert's opinions. The knowledge elicited from the medical expert was transformed into the following rules (see Table 1).

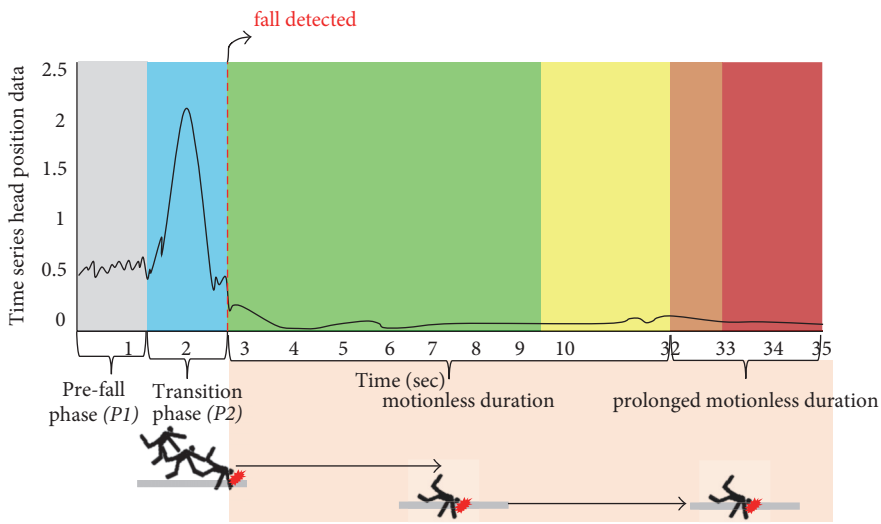
Additionally, in some cases where more than one body-joint position hitting the floor at the same time, we examined the duration of the motionlessness for the body-joint position



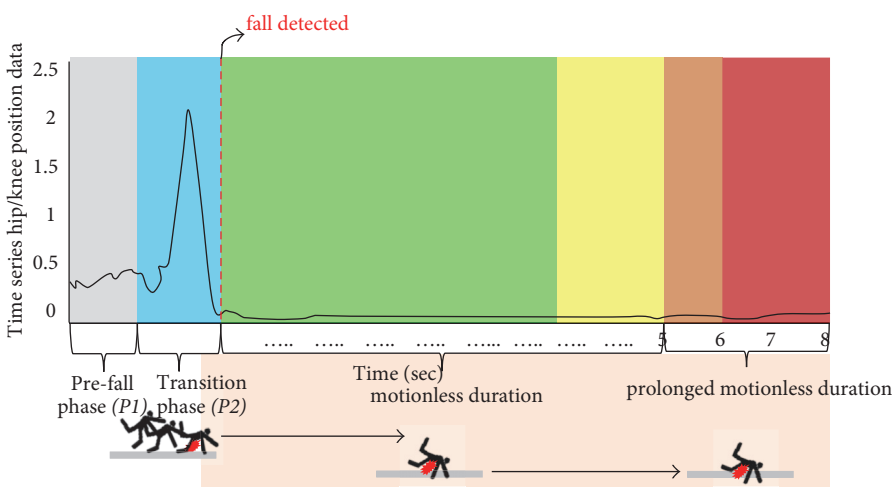
(a) General framework of three phases based on the segmented boundary



(b) Recovery phase



(c) Motionless duration based on the head hitting the floor



(d) Motionless duration based on hip/knee hitting the floor

Figure 4: Motionless duration detection after a fall.

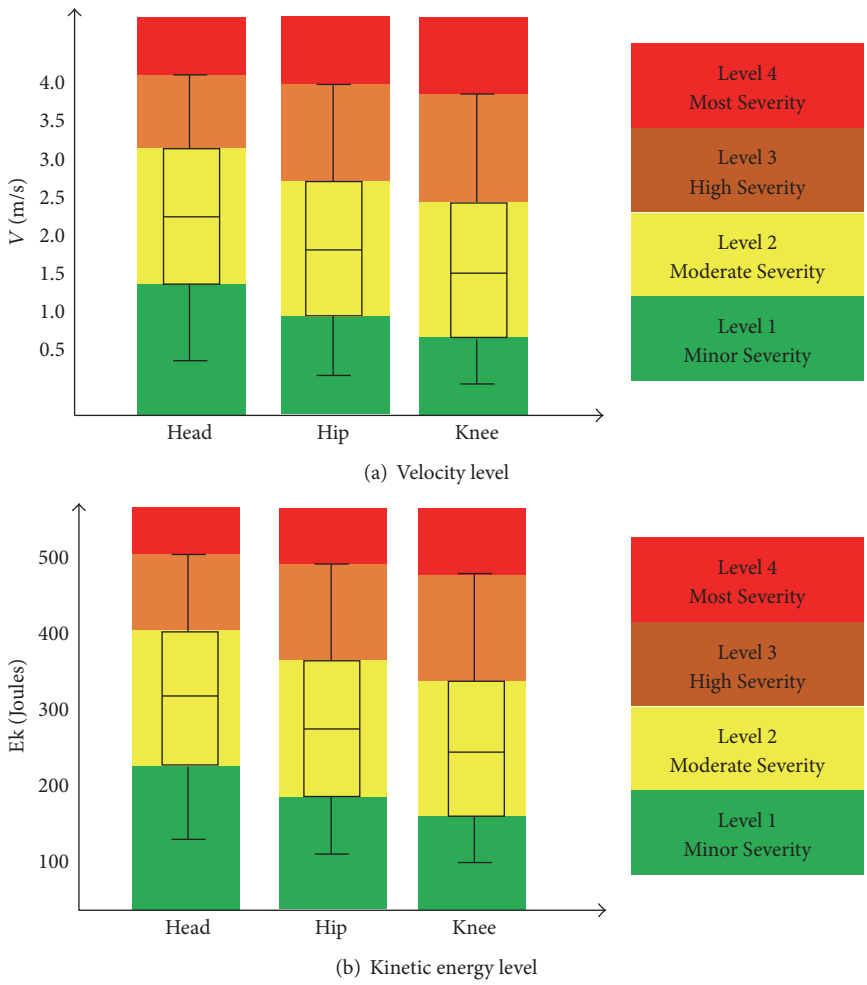


Figure 5: Fall severity criterion [4].

with the highest level of impact using body-joint fall impact algorithm (see Section 3.1.1(1)).

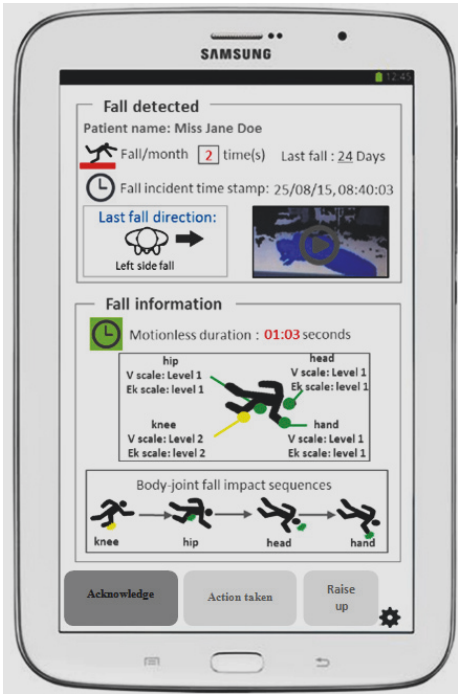
Finally, the remaining two fall severity factors (velocity on impact and kinetic energy on impact) are proposed in our previous work [4]. In order to describe velocity on impact and kinetic energy on impact of a consequent fall, the scale for fall severity estimation developed in our previous work (see Figure 5), called Fall Severity Injury Score (FSIS) to classify severity level of falls, is applied. The data set was trained to create a model similar to what is shown in Section 3.1.1(1).

3.1.2. Notification. Once a fall is detected and fall severity factors are computed, the system that provides message notifications to users will be automatically activated. It provides the updated status of the fall incident on a dashboard graphical user interface (see Figure 6). Generally, most people have electronic mobile devices such as smartphones and tablets. To make the system friendly and affordable, we developed a notification system that relies on heterogeneous communication channels such as a smartphone, tablet, or smart TV on an Android platform, which supports Android version 2.3 and later. The connection is through a hierarchical network using the push notification message concept via Transmission Control Protocol/Internet Protocol (TCP/IP) networking through Wi-Fi. Figure 7 shows the process flow for notification. Possible types of notification message are summarized in Table 2.

Figure 6(a) shows the monitor screen of the proposed system. The display is divided into 4 parts: online monitoring and captured images that present the current state of the subject (video clip), instant notifications and user interaction, patient information, and fall information.

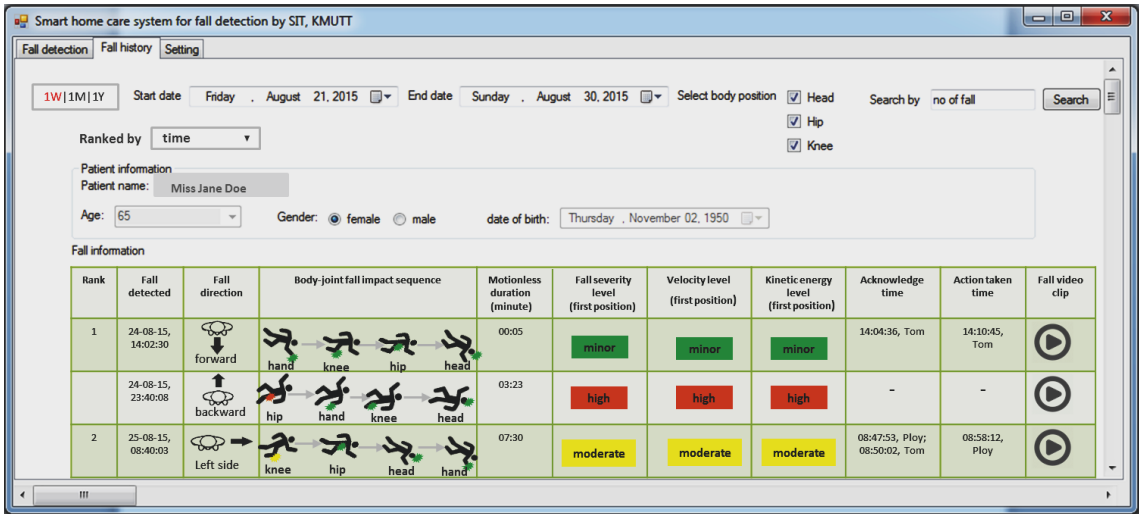
For the first part, the monitoring system is divided into two parts: online monitoring and captured images recorded during the fall. The first part is to record a stream of data representing time sequential frames of fifteen body-joint positions obtained from the Kinect for fall detection and is analyzed for fall severity factors in real time. The second part captures video of images occurring during the fall from the start of the fall until the end of the fall when subjects are laying on the floor by resampling every 5 pictures in 1 second, which are sent to the relevant persons (e.g., caregivers, family, and physicians). Video is planned to be available in 2 modes: Red, Green, and Blue (RGB) and depth image (see Figure 6(a)). The user can select either RGB or depth image. By default, the

(a) Main GUI for message notification via computer



(b) Main GUI for message notification via smartphone

Figure 6: Continued.



(c) Summary report of fall history

Figure 6: GUI for message notification.

Table 2: Types of message notification.

Number	Message	Receiver	Devices
#R1, #R2, #R3	Fall status, fall severity factors (e.g., velocity on impact, kinetic energy on impact, and body-joint fall impact sequences), fall video clip recorded during the fall	Caregiver and relevant persons	Computer, smartphone, tablet, or smart TV
#R4		physicians	

system was set up with depth image. Depth image is beneficial for subjects to preserve their privacy. However, in the medical expert's opinion, RGB is more beneficial for physicians to understand the circumstances of a fall (e.g., place, time of day, and subject's activity before the fall) and retrieval data to show fall mechanics. These fall mechanics can provide benefits in two aspects: extrinsic factors and intrinsic factors [31]. The first factor is beneficial for physicians to know environmental hazards which is cause of fall such as obstruction of furniture, wet floor, different level of floor, and house ladder. The second factor allows physicians to know about risky body conditions such as unstable joints, muscle weakness, visual problem, congenital disease, and drug side-effects. So, the physician can use these data to support decisions about physical therapy of body-joint fall on impact. In addition, the physician can suggest proper preventive exercise routine to reduce risk of severe injury in future falls.

Secondly, the system triggers an alarm and displays a message notification on several devices (see Figures 6(a) and 6(b)). This is very important and provides timely fall information that can support human judgment. Nevertheless, sometimes caregivers or relevant persons do not respond to notifications within the specified timeframe. The system records complete incident information that is useful for quality improvement, risk management, and peer review.

Thirdly, patient information is retrieved for viewing on a monitor screen to confirm personal identity and to be sure of obtaining the right information.

Lastly, fall information is divided into two parts: a fall event and summary report of a fall detection. The first part shows a fall event, which consists of different time between the current fall detected and previous falls detected, velocity on impact, kinetic energy on impact, body-joint fall impact sequences, duration of motionlessness after a fall, and a fall video clip captured during the fall. Note that different colors represent different response states: red for waiting response state, orange for not response state, and green for responded state. The second part is to report consequent fall detection and activity detection, which consists of the summary report of frequency of both fall detection and activity detection and frequency of body-joint position that is high impact acquired in the first part.

Additionally, we provide a fall history to further support fall severity diagnosis (see Figure 6(c)). The physicians can select a specific time period for which they want to view fall information such as week, month, or year. Fall information is ranked by time, fall severity level, and so on. The report shows fall information consisting of fall time stamp, fall direction, body-joint fall impact sequences, motionlessness duration, different colors representing different levels of fall severity, velocity, and kinetic energy: Level 1 = Green, Level 2 = Yellow, Level 3 = Orange, and Level 4 = Red, acknowledge time, action taken time, and fall video clip.

As shown in Figure 7, the message notification works in such a way that if a fall is detected, the notification system will be activated. The first notification with message #R1 will

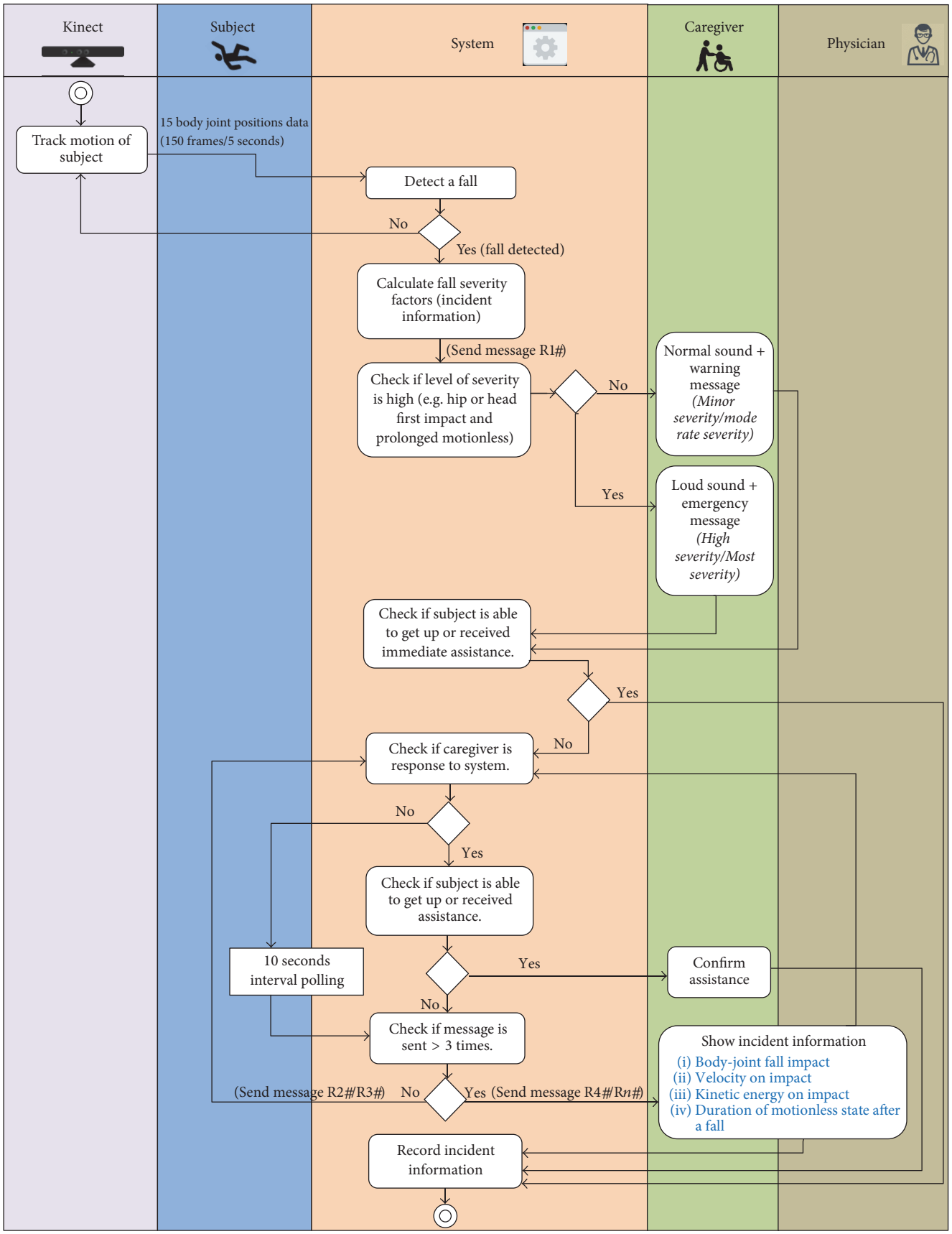


Figure 7: Process flow for message notification.

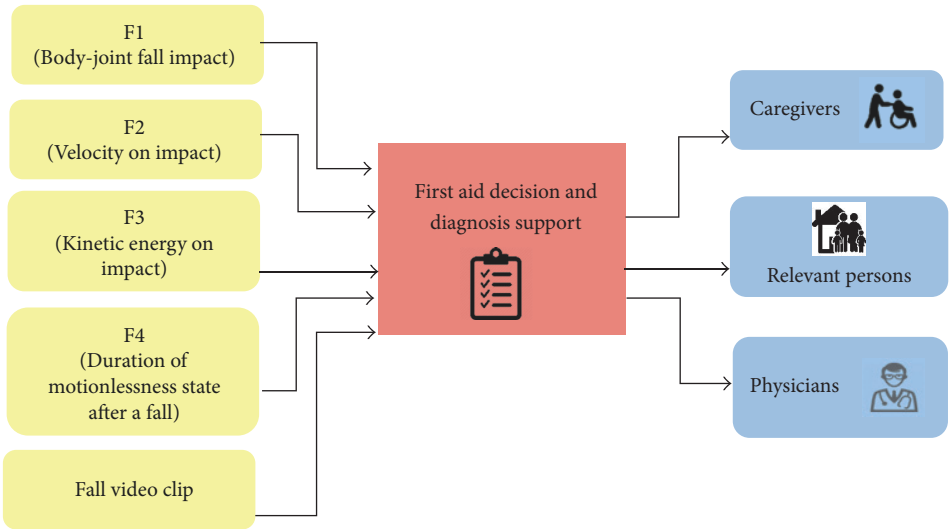


Figure 8: The modular structure for supporting decisions in first aid and diagnosis by caregivers and physicians.

be instantly sent to the caregiver and relevant persons. By a default setting of 10-second polling, messages #R2 and #R3 will be sent in sequential order to notify the caregiver and relatives if there is no sign of assistance or recovery. In the next polling onwards, if there is still no sign of improvement, message #R4 or above (#Rn, n = number of the polling rounds) will be automatically sent and brought up to a physician. The design of multinotification is to mitigate the effect of false positives, and the interval polling is to minimize the risk of injury or fatality.

The notification messages are divided into two types: normal warning message and emergency message. The message type and interval polling of notification are based on the severity level. Once the system detected that the subject is able to get up or receive immediate assistance, the system will record the incident information, and the application will resume its initial state. Note that the system allows users to subjectively select the interval polling of notification and number of notification messages. Appropriate settings should agree with the medical expert's opinion.

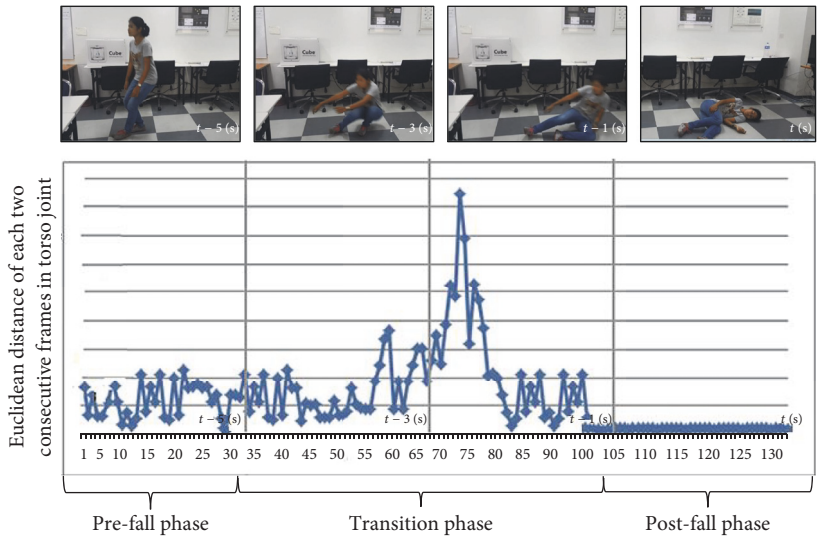
3.1.3. Fall Severity Intelligence Support. Once a caregiver (or relevant persons or physician) obtains a notification message, the ability to trace the chronological event and severity level of the fall to decide on aid (or to gain support for diagnosis) can proceed by hand. The number of fall severity factors given to support the judgment of caregivers, relevant persons, and physicians is four factors (e.g., expert opinion rules of body-joint fall impact (F1), velocity on impact (F2), kinetic energy on impact (F3), duration of motionless state after a fall (F4), and fall video clip recorded during the fall) as shown in Figure 8. In our system, caregivers and relevant persons use these factors to support strategic decisions about giving first aid and taking the fall subject to see a physician. Also, the physicians can utilize these factors to trace abnormalities of the subject's body condition that caused the fall and to support the diagnosis process for later treatment. It is especially useful for cases of subjects who are not able to respond due to a loss of consciousness or for cases of subjects who are able to get up but also frequently fall.

Figure 9: Experiment setup for post-fall intelligence system.

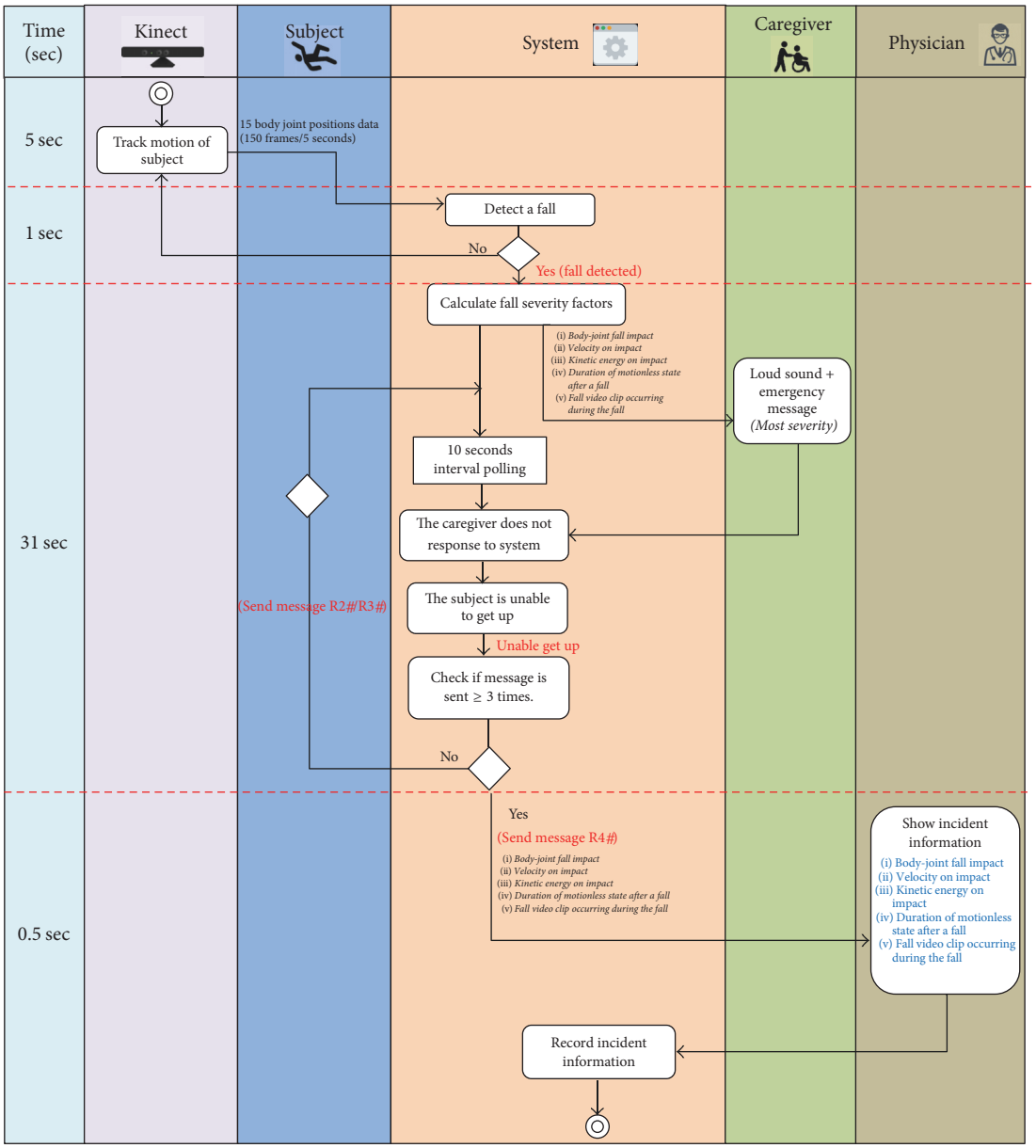
4. Experimental Results and Discussion

In this section, we explain the design of the experiment and show experimental results from post-fall intelligence.

4.1. Design of Experiment. In our experiment, we established an indoor environment setting with a Kinect to track the movement of sample subjects as seen in Figure 9. The setting is with some limitations, for example, a limited area of 5 × 7 m. in closed room and only young healthy adults were in these simulated falls which may not optimally robust to represent the condition of frail older adults. In real use, a physician may suggest some adjustment to fall monitoring system threshold values to be specific to elderly subjects. We performed preliminary experiments to select representative sample subjects for testing both accuracy and reliability

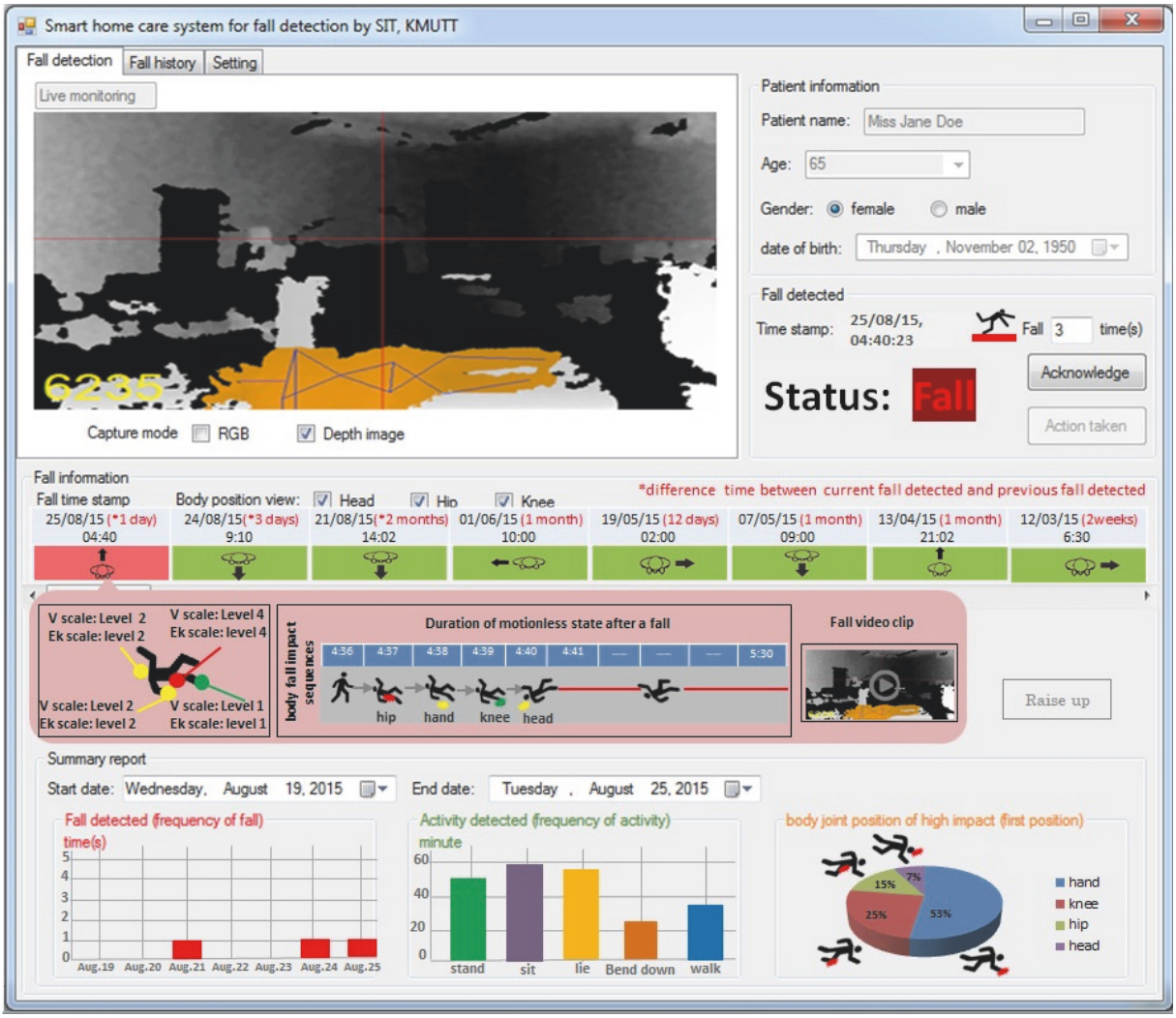


(a) The scenario of demonstration for fall detection with 5-second duration



(b) The derived factors and results severity for the case study

Figure 10: Continued.



(c) Monitor screen for the case study

Figure 10: The case study for fall detection and fall severity level estimation.

of the proposed system. The instruction with approval of the Institutional Review Board (IRB) of King Mongkut's University of Technology Thonburi was explained to the subjects for understanding the purpose of this data collection and experimental guideline as mentioned in Section 5. Every subject signed the consent form. We compared three factors: (1) gender, (2) body weight, and (3) height. Based on the results of our preliminary experiment, the alternatives of 18 possible cases (e.g., (thin, short), (medium, medium), and (fat, tall)) of sample subjects can be chosen. However, we found that some cases are not significantly different. To cope with such a varied sample of subjects for evaluation, there are 6 subjects (age 30 ± 8 years, body weight 75 ± 35 kg, and height 165 ± 15 cm with an equal number of males and females of various weights and heights). The fall monitoring system was tested with different types of falls (such as falling forward, falling backward, falling to the right, and falling to the left). We also evaluated the ability of the system to detect Activities of Daily Living (ADLs) including standing, sitting, lying down, and walking on a variety of seat types such as sofas, chairs with a backrest, and stools. The subjects performed all activities on safety mats.

4.2. Results and Discussion. To gain insightful experimental results, we conducted an experiment evaluating the fall severity level based on the results of fall classification (22 fall video clips from 24 simulated fall video clips). All of the 22 fall video clips consist of various situations of fall such as forward fall, backward fall, and left/right fall. The classification results are illustrated as a set of confusion matrix shown in Table 3.

As shown in Table 3, all 22 detected falls were further processed to classify the levels of severity, and an accuracy of 95.45% was reported. There was only one error (Fault Negative (FN)). The case was Level 2, but the system misidentified it as Level 1. This kind of error delays aid and could lead to even more severe injuries. This scenario was a backward fall. The person tried to sit down to attenuate the impact; hence, the velocity and kinetic energy of the fall were unintentionally

Table 3: Confusion matrix of fall severity level estimation using velocity and kinetic energy.

Actual	Prediction			
	Level 1	Level 2	Level 3	Level 4
Level 1	12	0	0	0
Level 2	1	6	0	0
Level 3	0	0	5	0
Level 4	0	0	0	0

softened. Moreover, to gain further insight into the effect of the case of FN, the two cases of undetected falls were considered. It was found that, in both cases, the severity was classified as Level 1, but the resulting velocity and kinetic energy were very low, which was similar to those of normal activities. There was almost no severity involved in either case. This means that the falls would not have any effect on the body, and this helped to assure us of the effectiveness of the proposed system. However, such data could still be utilized to raise awareness of abnormality of the falls that actually took place to yield support to further diagnoses and treatments.

5. Case Demonstration to Show Effectiveness of the Post-Fall Support System

In this section, we demonstrate how the proposed system will systematically and effectively work on a specifically situated case. Our established environment setting of demonstration is as defined in Section 4.1. In this demonstration, the subject was a female (age 31 years old, body mass of 50 kg., and height of 159 cm.). The plot of the demonstration was to let our subject simulate a severe case (highest severity level) of accidental slip, which caused the hip hit to the floor with great force. After the fall, the subject acted as if she could not move for longer than 30 seconds. The first 5 seconds of the fall event was recorded and is shown in Figure 10(a).

How the system instantly responds to the situation of a fall to support responsible personnel assisting the subject is as illustrated in Figures 10(b)-10(c). As shown in Figure 10(b), in a second, the intelligence system can complete the analysis of data streamed from Kinect and learn that subject had fallen with the hip position hitting the floor. Then one second later, the system could identify the severity and impact sequence of the fall (1st hit = hip (level 4 severity), 2nd hit = hand (level 2), 3rd hit = knee (level 1), and 4th hit = head (level 2)), and it instantly notified relevant persons (both caregiver and family) of the occurrence of the fall via the preassigned electronic channels. The notification came in a multimedia format of sound alert, fall video clip, and important analytic data (online and offline records) which was adaptively shown on a well-organized dashboard graphical user interface (GUI) on relevant persons' devices as seen in Figure 10(c). The system also monitored the response of any notified person and routinely repeated notification in cases in which no one acknowledged the event. Any progress, for example, a person pressing the buttons of "acknowledge" or "action taken," resulted in the displays of all persons being automatically updated with traceable records. In addition, a person can recheck directly with physician by pressing the buttons of "raise up" to confirm fall severity consequence regardless of whether the subject is able to get up or has received immediate assistance.

In a simulated case of highest severity, if the subject could not get up for quite a long time, or beyond the 10-second interval polling between the notifications, the system notified the caregiver and relevant persons 3 times (#R1–#R3 messages) before elevating the severity level and automatically alerting the physician (#R4) or above (#R*n* message). However, if the subject self-recovered or got first aid from the caregiver or relevant persons before #R4 activated, the incident was recorded and the application went back to its initial state.

In addition to the first two contributions ((i) severity and impacting sequence of fall analysis and (ii) systematical notification and first aid support) of our post-fall intelligence, next we demonstrated the third contribution of diagnosis support for further treatment. The latter contribution is helpful to the physicians, especially, if the subject was unable to respond due to loss of consciousness or was conscious but unable to recall the incident details. In Figure 6(c), the current and historical records of falls (packed with the analytical results as illustrated above) plus the recorded collaborative actions during the notification and first aid support can be retrieved/sorted by impacted body parts or by time period.

Overall, the demonstration shows that the framework of our post-fall intelligence system enables effective post-fall analytic and diagnostic support to caregivers and physicians when taking care of the fall subject for instant first aid and later treatment.

Finally, in the future work, we have planned to conduct more detail formal interview with caregivers and rehabilitation physicians based on questionnaires. In this study, we have only informally demonstrated the system and interviewed six caregivers and a rehabilitation physician to ask for their overview feedback on the direction of future system usability study. The caregivers strongly agreed that our post-fall intelligence can provide valuable incident information because the system contains recorded incident information of both current fall information and fall history by week, month, or year in all cases even though the caregiver or relevant persons may not be with the elderly during a fall or the fall may have been forgotten by the subject. The physician was also satisfied and showed the intention to use the system because the data that were derived from the system could support the diagnosis. The physician could focus the diagnosis on body-joint position of the injury to ensure prompt treatment. Therefore, based on the findings, it could be concluded that physicians will be able to quickly and accurately diagnose the subject, particularly during an emergency situation in which the subject requires immediate attention and assistance.

6. Conclusions and Future Works

We proposed a post-fall support system, designed to systematically connect with unobtrusive monitoring of falls

(Kinect or depth-camera based system). The post-fall support system provides a three-part contribution. The first is to investigate fall severity factors and the impact sequence of body parts based on expert opinion rules. The second is to send a fall message to the caregivers and relevant persons via electronic channels, for example, a smartphone, tablet, or smart TV set, and provide a systematic collaborative platform for all relevant persons. The last is to provide online analytic information that supports the diagnostic process of caregivers and physicians for giving instant assistance to the fall victim and making a decision on further medical treatment.

In the experiment, the results obtained in the fall severity level classification prove that our system yields a satisfactory performance of 95.45% accuracy. The post-fall demonstration illustrates an extreme case of post-fall intelligence and gives insight into how the proposed system is beneficial to the diagnostic and posttreatment decision process for the relevant persons (e.g., caregivers, family, and physicians), especially in cases in which incident information is otherwise unavailable. The caregiver or relevant person is timely notified and supported to make an informed decision to take care of the fall subject. This can help to effectively reduce risks of injury and fatality as well as enhance the quality of life of fall subjects. Last but not least, the ability to provide timely and traceable incident information for supporting the physicians' diagnosis for treatment can make their work faster, more accurate, and more effective, particularly for subjects who have fallen down and are unconscious and unable to respond or are conscious but cannot recall the incident details.

However, this work still has some limitations. Firstly, a single Kinect camera is with limited viewing angle. This might lead to inaccurate body-joint positions in some situations, for example, viewing angle not exposing both sides of the body, part of the body being occluded, or sunlight effect. Secondly, the system was tested by younger healthy adults and only under the controlled environment. These concerns shade some challenging issues for future work. Some modules should be added, for example, environmental assessment, gait assessment, multiple Kinects, and integrative model with alternative sensors (smartphone based on gyroscopes [32, 33]). This should enhance the analytic information provided to physicians when conducting diagnosis for causes of falls and their treatment. Another idea is to extend the scope of involvement to include more medical healthcare staff members (e.g., physicians, nurses, or other medical staff) for better collaboration.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by Rajamangala University of Technology Krungthep. The authors thank students and staffs of the School of Information Technology (SIT), King Mongkut's University of Technology Thonburi, for their invaluable assistance in setting up the experimental environment for the capturing sessions.

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