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Bed-Exit Prediction Based on 3D Convolutional Neural Network

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***Abstract*—This paper presents a vision-assisted human motion analysis method that can be used to recognize in-bed preparatory motions for bed-exit. In this work, a 3D convolutional neural network was applied to predict sequential motions from ultra-low resolution (32 × 24 pixels) clips composed of depth images, which meets both privacy and computational efficiency requirements. The experimental results showed that the system effectively recognized key motions of bed-exit before bed-leaving. Moreover, these motions were applied to bed-exit prediction in several cases of disturbance and for beds of different structures, and the system accurately predicted bed-exit.**

Keywords—bed-exit, machine learning, depth image, 3D convolutional neural networks.

I. Introduction

For elderly patients, falls are a major cause of accidental injury and death in hospitals and nursing homes [1], and commonly occur when patients intend to leave their bed [2]. The involvement and assistance of nursing staff can reduce the risk of falls during bed-exit. To further prevent injuries related to falls, hospitals and nursing homes have increased demands for bed-exit detection systems [1, 2] that sound an alarm when a patient intends to leave their bed.

In previous studies, one approach was the design of a pressure-sensitive system, which consisted of pressure mats [3]. Another technique employed depth cameras [4, 5], and other solutions have included wearable sensors such as accelerometers [6, 7] and RFID sensors [8]. However, most of the existing bed-exit detection systems focus on the monitoring of bed-exiting and falling behaviors. In practice, falls may occur soon after a patient exits the bed. Thus, if an alarm system issues an alert signal after a patient has sat up or exited the bed, it may then be too late for nursing staff to respond to.

To provide an early warning, some researchers have proposed bed-exit prediction schemes based on the hidden Markov model (HMM) to recognize the sequence of preparatory movements before the patient exits the bed [5, 6], which employs sequential depth images and motion data. However, wearing sensors is uncomfortable and inconvenient for patients. In addition, applying high-resolution color or depth images in order to recognize activities of patients raises privacy concerns.

In our previous work [9], a convolutional neural network (CNN) of deep learning was used with low-resolution depth images to avoid privacy concerns. This work utilized recognition of static postures to predict bed-exit. However, two prediction problems were present and needed to be overcome: first, the system generated a false alarm if the patient remained sitting in the bed without any intention to leave the bed; and second, the scenario in which the patient directly sits on the bedside after rolling towards the edge of bed from a lying posture. In our previous research [10], we identified two key intermediate motions between the aforementioned initial and terminal postures. This discovery can be used as an inspiration to assist recognition of motions as early warnings in future studies. To solve the above problems, a 3D CNN model [11] was adopted in this paper. This paper utilized sequential and low-resolution images to recognize motions; in addition, we proposed an online bed-exit prediction system, evaluation of which demonstrated that the method is feasible.

II. Methods

A. Motion States of Bed-Exit

According to our previous research [9, 10], we generalized the in-bed activities related to the bed-exit process. There are two main branching scenarios for bed-exit before sitting on the edge of the bed and leaving the bed. One of the motion states is turning of the waist in the bed (TWB) after sitting up. Another motion state is rolling toward the edge of the bed (REB) after lying. A state diagram of bed-exit motions is presented in Fig. 1.

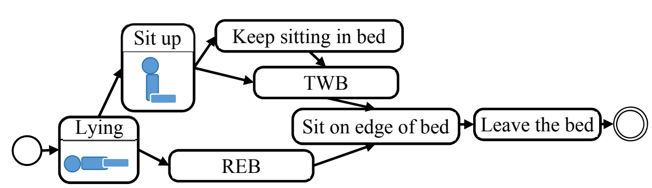

Fig. 1. State diagram of bed-exit motions.

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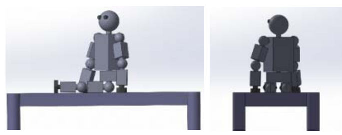
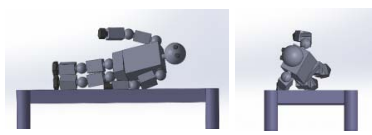
B. Identifying the Existence of Motion States Using CNN

The CNN architecture was used to identify the existence of TWB and REB motion states through different training and test samples of static postures [10]. In the two different trained models, the two postures of TWB and REB can be identified, as shown in Fig. 2 and Fig. 3, respectively.



(a) (b)

Fig. 2. Posture of TWB motion: (a) left side view, (b) rear view.



(a) (b)

Fig. 3. Posture of REB motion: (a) left side view, (b) rear view.

The CNN model of TWB was analyzed by visualization of CNN feature maps. The activation motions of the first layer were both "sit up" and "sit on edge of bed"; there were no TWB motion states. In the feature maps of the second layer, more activations of the TWB motion state was found (about 48% of the total). This result showed that the motion of TWB was more complex and difficult to classify than "sit up" and "sit on edge of bed". Similar results occurred for the CNN model of REB.

C. 3D CNN Architecture

Bed-exit behavior consists of continuous motion, and the key motion postures of each person are slightly different. There remains a certain difficulty in terms of only relying on a single image to determine the bed-exit action. Nevertheless, recognizing motion states from continuous data can reduce the effects of differences in individual actions. As a result, recognition of or even prediction of motion states according to sequential images is more reliable. A 3D CNN was adopted to recognize the five motion states during bed-exit. The 3D CNN architecture consisted of four convolutional layers (filter kernel size: $5 \times 5 \times 5$), three subsampling layers, and three fully-connected layers, as shown in Fig. 4. The size of the input image was $10 \times 24 \times 32$ (depth × height × width), and the output had five nodes for five classes of motion states. The input was convolved with 32 filters by a convolutional layer (C1), and each feature map was the same size as the input. The following subsampling layer (S2) was implemented with max pooling, with a size of $1 \times 2 \times 2$ and a stride of $1 \times 2 \times 2$. Subsequently, the 64-filter convolutional layer (C3) was the same size as the output of the S2 layer ($64 \times 10 \times 12 \times 16$), and the following subsampling layer (S4) had the same size and stride ($2 \times 2 \times 2$). The C5 and C6 layers convolved with 128 filters. Subsequently, the S7 layer had the same stride as S4, and the output of the S7 layer was $128 \times 3 \times 3 \times 4$. The S7 layer was fully connected to the F8 layer. F8 was fully connected to the F9 layer, and then F9 was fully connected to the F10 layer. Finally, the F10 layer was connected to the five nodes of output. The output nodes represented five classes of motion states: lying, sit up, TWB, REB, and sit on edge of bed.

III. Experiments

A. Experimental Setup

In order to address the needs for gas, electricity and other services that may be required in hospitals and healthcare centers, the head of a patient's bed is usually close to a wall. For bed-operating efficiency, a depth camera was deployed on the wall close to the head of the bed, similar to the configuration of a real patient room. The bed size was 100 × 193 cm, as shown in Fig. 5. The vertical distance between the depth camera and bed was 57 cm. The field of view of the depth camera was 68 degrees, which covered the limbs and trunk of a person lying on the bed. The laptop computer on the right side of the bed head gave real-time output prediction results. After processing of the depth camera clips, the dimension of each clip input to the 3D CNN was $10 \times 32 \times 24$ (clip length: 10 frames; image resolution of each frame: 32×24).

1) Experimental Setup of Training: To generate diversity and sufficient training samples, each training clip with 10 frames (according to the depth setting of the 3D CNN) was clipped from a long clip with a stride of 1. For instance, if a long clip length was 30 frames, we were able to generate 21 clips of training samples from the long clip. The parameters of the 3D CNN and training samples are shown in Table I.

TABLE I. Parameters Of Training

Number of training samples	33,456
Lying clips	12,283
Sitting clips	10,723
TWB clips	2,059
REB clips	357
Sit on edge of bed clips	8,034
Batch size	50
Epoch	10,000
Dropout rate	0.5

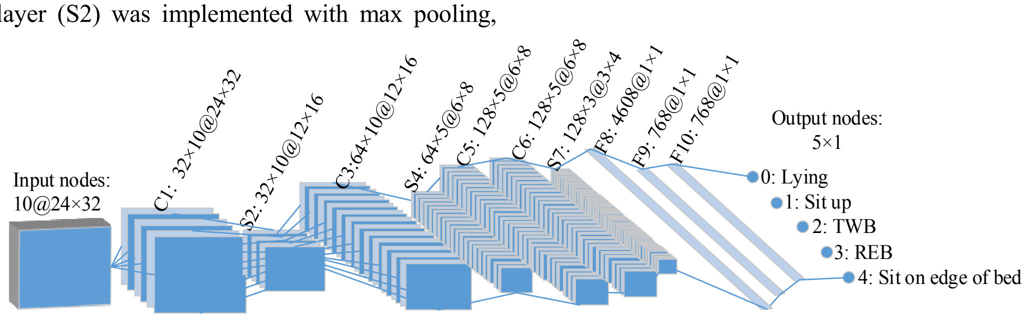


Fig. 4. 3D CNN architecture.

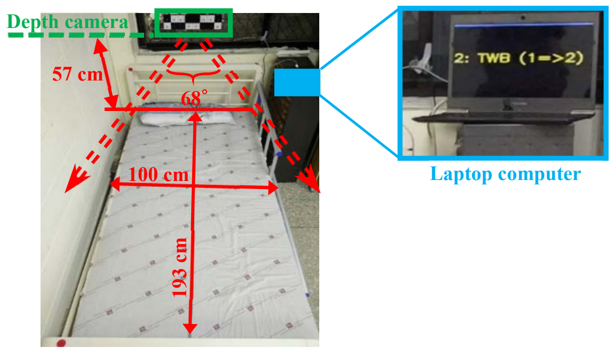


Fig. 5. Setup of bed and depth camera.

2) Experimental Setup of Real-time System: To infer and load the trained model, we integrated TensorFlow Serving into the prediction system flow, as shown in Fig. 6. The "required frames" was defined as 10 frames, and the system captured 30 frames per second from the depth camera; this presented a new prediction result per 5 frames. Two consecutive depth clips overlapped by 5 frames, because the last process of the system flow removes 5 frames (half the number of required frames) from the queue in each loop. The system was executed using an Intel CPU (i5-3317U) and 10 GB of RAM; no GPU acceleration was used for inference of the trained model.

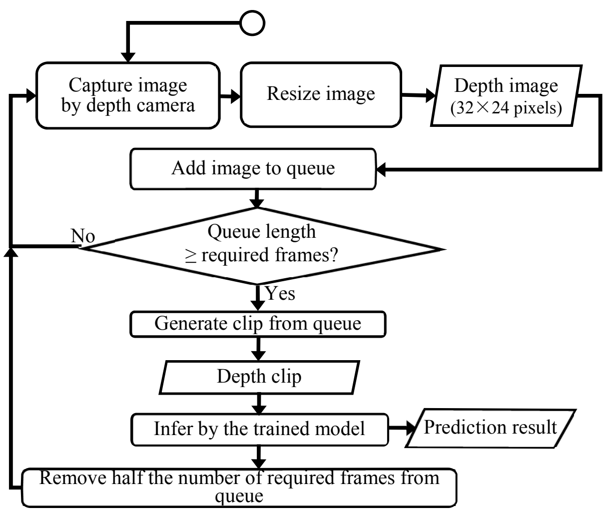


Fig. 6. System flow of bed-exit prediction.

B. Experimental Results of Real-time Prediction

Subsequent experiments were performed to evaluate bed-exit behavior from "lying" to "sit on edge of bed" without leaving the bed, which lasted for approximately one second (30 frames) before the patient completely exited the bed. The time required to perform the bed-exit process varies in different patients with different conditions, the elderly and patients with a physical illness requiring a lot more time to completely leave the bed. The following three experiments demonstrated the online and real-time inference of the activity in bed and recorded live on videos [12] synchronously.

1) Sit Up to TWB with Bed Rail: The online inference is shown in Fig. 7. The snapshots in the first row present moments of different bed-exit actions in the experimental scene. The second row shows different groups of clips from the input depth images, corresponding to different actions. Each tag in the third row indicates the online recognition results of the system. For instance, at the moment of latest frame 330, the subject lay down on the left side, and the system recognized the input clip (from frames 321 to 330) as "lying". Therefore, in subsequent experiments, "LF" denotes the moment of the latest frame. When the subject turned around in bed, the system recognition result remained at "lying". The system did not recognize it as any other action, nor a result of other actions. It wasn't until LF 455 that the action of the subject changed to "sit up". In the meantime, the motion state had begun to change, and hence the recognition result was "sitting" until LF 455. During frames 451 to 460, the action was recognized as TWB, the correct motion state for bed-exit prediction. After LF 470, it was recognized as "sitting", because the subject needed to move the body forward to avoid the bed rail. In the second TWB interval, when the subject had moved to the second half of the bed, the subject needed to again turn the waist to turn the body sideways. When the system recognized the subject sitting on the edge of the bed, the motion state changed from TWB to "sit on edge of bed" (LF 505).

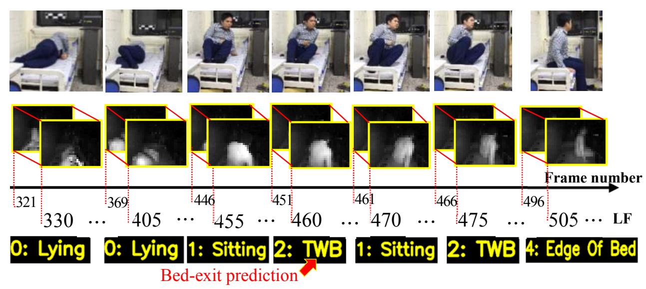


Fig. 7. Sit up to TWB for bed-exit prediction.

2) Keep Sitting to TWB with Bed Rail: Before TWB during the bed-exit process, the most complicated and diverse motion state is "keep sitting in bed". The first experiment (LF 355–490), shown in Fig. 8, was performed to evaluate whether, while the subject was "lying", activities around the bed would interfere with the performance of the system. In the first case (LF 355–410), a person walked beside the bed several times, and in the second case (LF 490), a person sat directly on the bed at a position in which the subject could be recognized as of the state "sit on edge of bed". In both cases, the proposed system successfully recognized the subject as "lying on the bed", while pressure sensor-based systems would be likely to mistake the second case as leaving the bed. The second experiment (LF 620–1200) was performed to evaluate whether various activities performed by the subject sitting on the bed would impact the recognition result. These activities were sitting up (LF 620), leaning to the right while the arms supported the body (LF 700), leaning to the left (LF 740), moving backwards (LF 985), moving forwards and sitting cross-legged, and then turning toward the edge of the bed (LF 1200). All of the activities above are difficult to recognize using pressure sensor-based systems, but the proposed system consistently recognized the patient as sitting up. In the last experiment (LF 1385–1475), the subject performed a complete bed-exit process with the

TWB scenario, which was similar to the bed-exit process described previously in subsection B1. The proposed system correctly recognized TWB at LF 1435 and performed bed-exit prediction.

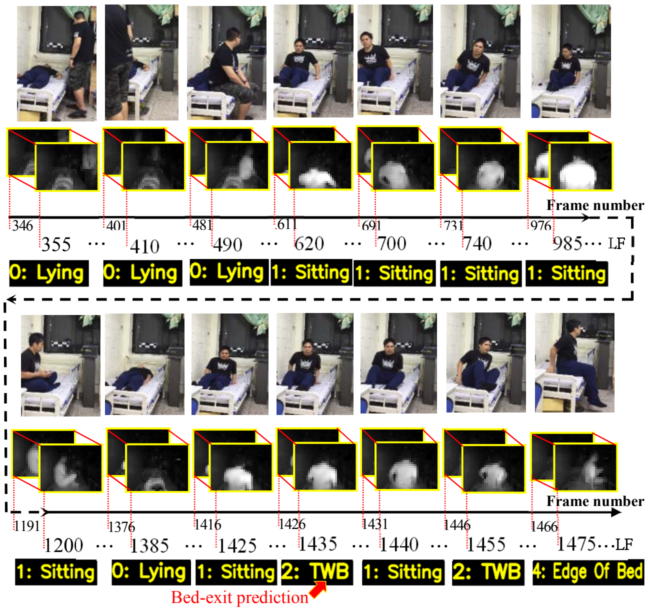


Fig. 8. Keep sitting to TWB for bed-exit prediction.

3) Lying to REB without Bed Rail: In most family or nursing homes, the beds do not usually have a bed rail. Users prefer to leave the bed through the REB scenario, because these kinds of bed have no bed rails to hinder, as shown in Fig. 9. At LF 235, the subject was lying on the bed with their knees up, and the system did not recognize the knees-up motion as "sit up". At LF 250, the subject was lying on the side of the bed, and the system correctly recongnized the subject as "lying". In LF 330–345, the subject's motions were correctly recognized as REB and "sit on edge of bed". However, using sensors of the load cell type, it was difficult to recognize REB motion, because the force distribution of the motion is similar to that of turning sideways during normal sleep.

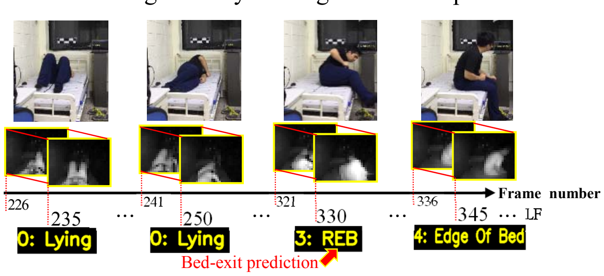


Fig. 9. Lying to REB for bed-exit prediction.

IV. Conclusion

This study demonstrated that the 3D CNN was able to classify complex human motions in bed. The capability of recognizing motion in bed can be applied to bed-exit prediction, even using low-resolution depth clips; accordingly, the use of low-resolution images avoids privacy concerns. The installation position of the camera was limited by the realistic hospital conditions, and not all limbs could be observed after sitting. These two prerequisites make the design more difficult, but render the system easier to apply practically. Also, evaluation showed that detection of difficult scenarios can be easily accomplished using low-resolution depth images, which differs from other types of sensor, such as pressure sensors.

While the proposed system can recognize the rapid bed-exit process of healthy adults, it lacks training and testing in the elderly and in patients with a physical illness. From the experimental results, we consider that if the system was implemented in hospitals and nursing homes, it would provide much earlier notification, allowing the nursing staff time to react.

Acknowledgments

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