Behavior Classification for Bed Monitoring Using Short-Term 60 GHz-Band FMCW Radar Images

Shuhei Hashimoto[1,*], Xiangbo Kong[1], Kazuhide Kamiya[1] and Kenshi Saho[2,*]

[1]Department of Intelligent Robotics, Toyama Prefectural University, 5180 Kurokawa, Imizu, Toyama, Japan
[2]Department of Electronic and Computer Engineering, Ritsumeikan University, 1-1-1 Noji-Higashi, Kusatsu, Shiga, Japan

Abstract

This paper shows a practical 60 GHz-band radar-based method to recognize behaviors for bed monitoring systems. Time-range images, derived from short-term data, were produced through the processing of frequency-modulated continuous-wave (FMCW) radar signals. Using the generated images, behaviors such as leaving the bed, lying on the bed, and sitting on the bed were accurately classified with a classification accuracy of 96% using a convolutional neural network with a relatively light-sized model of MobileNet. Furthermore, six representative behaviors in bed monitoring were classified with an accuracy of 83.1%. These findings indicate that 60 GHz-band millimeter-wave radar holds promise as a non-invasive bed monitoring tool.

Keywords

Millimeter-wave radar, 60 GHz FMCW radar, Human activity recognition

1. Introduction

In the elderly care sector, the shortage of careers relative to the number of individuals requiring assistance has led to an increased burden on each caregiver. Consequently, round-the-clock monitoring in nursing homes to prevent falls or wandering is required and is contributing to caregiver workload. Previous researches have focused on sensor-based monitoring systems to track bed-bound behaviors, with early detection of bed-leaving being crucial for identifying abnormal situations. These systems have employed various devices such as cameras, pressure sensors, wearable sensors, and infrared cameras [1, 2]. While pressure sensors are easy to install and are easy to detect bed-leaving, their accuracy for the behavior classification is insufficient. Wearable sensors require caregiver assistance for attachment and removal, adding to their workload. Camera systems, including Infrared cameras, offer non-contact monitoring but raise privacy concerns and installation challenges within private rooms.

To tackle the above problems, recent research has explored the integration of radar technology into monitoring systems designed for the elderly [3, 4]. Radar technique enables non-contact measurements of the distance and velocity information, and can operate effectively in low-light

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*Corresponding author.
u354018@st.pu-toyama.ac.jp (S. Hashimoto); saho@fc.ritsumei.ac.jp (K. Saho)
0000-0003-2088-1231 (K. Saho)

conditions. It does not raise privacy concerns because it does not capture visual data. Recently, mill-meter wave radar techniques have achieved accurate human pose detection [5, 6]. However, such techniques require long-term data and processing with heavy computational load.

Thus, we developed a bed-leaving detection method using short-term radar data [7]. We used millimeter-wave radar images, which fully contain range and velocity information of human body parts, to classify human behaviors related to bed-leaving and bed-lying. By applying frequency-modulated continuous-wave (FMCW) radar signal processing, time-range (time-distance) and time-velocity images were generated as the input of machine learning-based behavior classification models. Accurate classifications were demonstrated using the images corresponding to short-time data for real-time monitoring systems for nursing homes. As a result, the convolutional neural network (CNN) utilizing time-range images accurately classified bed-leaving and other behaviors, including sitting on the bed, with over 90% accuracy. However, this study conducted only binary classification, e.g., a simple classification of two classes of bed-leaving and bed-lying; results are lacking in terms of developing a monitoring system that includes a variety of behaviors.

In this paper, we report the experimental results for multinomial classification of human behaviors for bed monitoring. We assume six classes of behaviors related to bed-leaving and bed-lying activities. Classification accuracies using practical CNN models with the inputs of the short-term time-range images were evaluated for 10 participant data.

2. Radar Experimental Setup

Figure 1 shows the experimental setup. A 60 GHz FMCW radar was installed at a height of 40 cm from the surface of the bed. The radar bandwidth was B = 6.8 GHz, the range resolution was $\Delta R = c/2B = 2.4$ cm (where c is the speed of light) and its frame rate was 80 Hz. Radar directivity in a plane parallel to the bed surface was 120°.

The participants were ten young adults. Instructions were given before measurement and each behavior was measured for the 60 s with the pulse repetition interval of 80 Hz. Our experiments aim to classify representative behaviors on and around the bed via the unstrained measurements using the radar. The assuming behaviors were "bed-leaving", "bed-lying", "sitting square", "long sitting", "standing outside" and "lying outside". Fig. 2 shows the experimental sites for some classes. Each behavior is defined as follows.

- bed-leaving: A participant is not in the radar measurement area.
- bed-lying: A participant is lying on the bed. This includes the participant's slight motions in the bed.
- sitting square: A participant is sitting on the edge of the bed.
- long sitting: A participant is sitting with extended legs on the bed.
- standing outside: A participant is standing by the bed.
- lysing outside: A participant is lying on the floor by the bed. This class assumes abnormal situation.

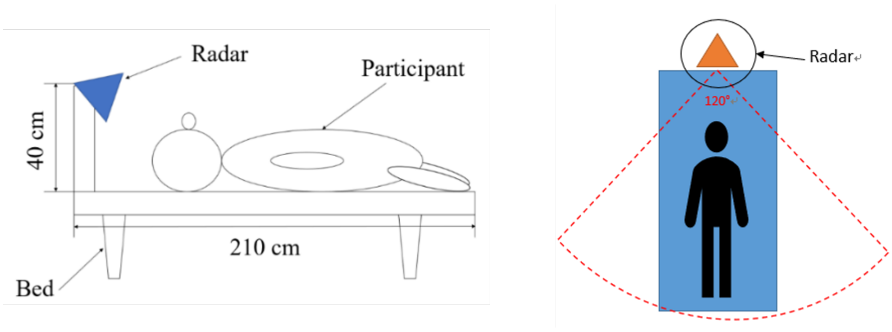

Figure 1: Experimental setup

Figure 2: Experimental sites for "lying outside", "standing outside, ""sitting squire", and "long sitting".

3. Generation of Time-Range Images

To classify the behaviors, we calculate the time-range distributions from the radar received signals similar to our previous work [7]. We obtain time-range distribution images by Fourier transform of the received signal corresponding to each pulse transmission. For every 0.5 seconds, a 224 × 224 PNG image with horizontal axis of time and vertical axis of range was generated whose color corresponds to the received power.

Fig. 3 shows the examples of time-range images of the six classes. In these images, the vertical axis means that the lower part of the image is further away. There are no significant components in the "bed-leaving" image because the participant does not exist in the measurement area. The "lying outside" image is similar to "bed-leaving" except for the slight components in a relatively far range. We can confirm the similar significant components in the "bed-lying", "sitting square", and "long sitting" images. In the "standing outside" images, the significant components are confirmed in far range compared with "bed lying". We used these images for the CNN inputs to classify the six classes based on the slight differences described above.

4. Results and Discussion for Behavior Classification using CNN

In this section, the classification results for representative behaviors related to bed-leaving and -lying movements are presented. For each classification, the data to evaluate classification performance was obtained from 10 participants, and the mean classification accuracy in the

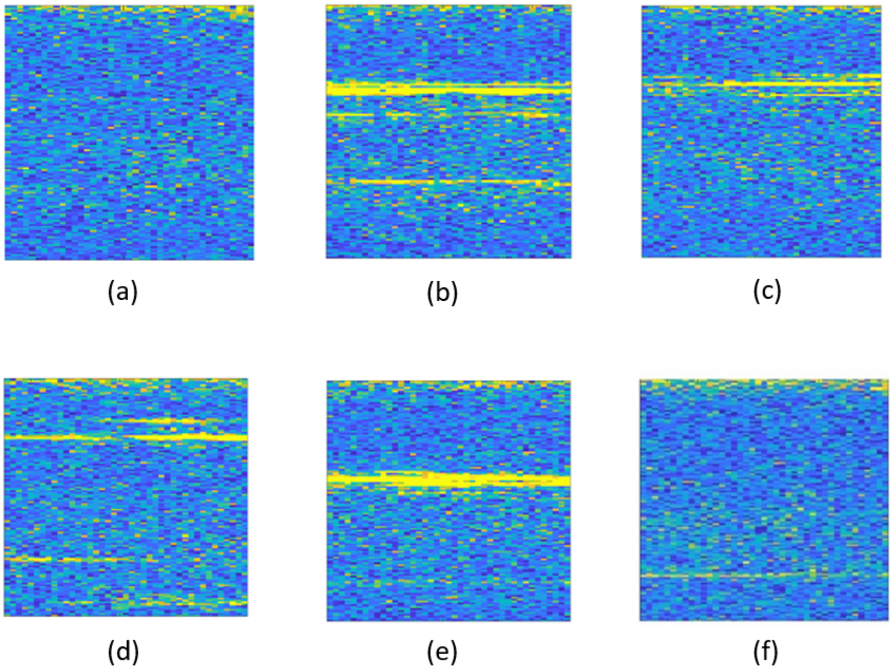

Figure 3: Examples of time-range images for six behaviors: (a) "bed-leaving", (b) "bed-lying", (c) "sitting square", (d) "long sitting", (e) "standing outside", (f) "lying outside".

leave-one-subject-out was evaluated. We generated about 100 time-range images corresponding to each behavior for all participants.

The behavior corresponding to each image is classified using the CNN. For the CNN architecture, we used the ResNet-18 [8] because it was demonstrated to be efficient for radar-based human activity recognition problems [9]. This study used the ResNet-18. In addition, we also used MobileNetV3 [10] because the ResNet model size is relatively large, and a smaller model size is required for practical use based on edge computing. For both models, we performed training for 50 epochs and used a batch size of 64. The learning rate was 0.01 and was decreased by multiplying it by 0.5 every ten epochs. These hyperparameters were empirically optimized.

4.1. Classification of Bed-Leaving and Other Behaviors

Because the detection of bed-leaving is the most important function for daily bed monitoring systems, this subsection considers the classification of bed-leaving and other five behaviors. Table 1 shows the results for the ResNet with a mean classification accuracy of 97.8%. Sufficient accuracy was achieved, and the rate of misclassification of bed-leaving as other behaviors is lower. The result is considered safe in terms of developing a monitoring system. Table 2 shows the results for the MobileNet with a mean classification accuracy of 95.9%. Although the accuracy of MobileNet is lower than that of ResNet, sufficiently accurate detection of bed-leaving is achieved even when using MobileNet with a smaller model size.

Table 1
Confusion matrix for the classification of the bed-leaving and other behaviors (ResNet).

Predicted \True	Leaving	Other behaviors
Leaving	99.8 %	4.3 %
Other behaviors	0.2 %	95.7 %

Table 2
Confusion matrix for the classification of the bed-leaving and other behaviors (MobileNet).

Predicted \True	Leaving	Other behaviors
Leaving	97.3 %	5.5 %
Other behaviors	2.7 %	94.5 %

Table 3
Confusion matrix for the classification of all 6 classes (ResNet-18).

Predicted \True	bed-Leaving	bed-Lying	sitting square	long sitting	standing outside	lying outside
bed-leaving	99.6 %	1.6 %	0.3 %	0 %	0 %	15.0 %
bed-lying	0 %	89 %	0.9 %	16.1 %	0 %	0.2 %
sitting square	0 %	0.9 %	68.5 %	12.7 %	2.4 %	0.1 %
long sitting	0 %	6.9 %	13.6 %	54.1 %	0.4 %	10.1 %
standing outside	0 %	0 %	13.9 %	2.3 %	94.9 %	4.7 %
lying outside	0.4 %	1.6 %	2.9 %	14.8 %	2.4 %	69.9 %

4.2. Multinomial Classification of Behaviors

We classify six behaviors to develop more useful multinominal behavior classification functions for the bed monitoring systems. Table 3 shows the results for the ResNet, with a mean classification accuracy of 89.7%. As indicated in this table, the classes "sitting square" and "long sitting" were misclassified because the features of these classes were not sufficiently expressed in the time-range image. In addition, "lying outside" was also largely misclassified because the part of the participant was out of measurement area, and it concluded time range images included less information. However, the important classes of "bed-leaving" and "bed-lying" were accurately classified. Thus, we achieve the behavior classifications with moderate accuracy even using the images generated from short-term data of 0.5 s.

Table 4 shows the results for the MobileNet with the mean classification accuracy of 68.5%. Because MobileNet is a simple CNN model, classification accuracy is lower than that of ResNet. However, the model sizes of the ResNet and MobileNet in this study were 18.0 and 0.2 MB, respectively. Thus, the performance improvement using the MobileNet is important future study to develop practical bed monitoring systems with simple implementation. Multiple images corresponding to multiple receiving antennas can be used to improve the classification performance.

Table 4
Confusion matrix for the classification of all 6 classes (MobileNetV3).

Predicted \True	bed-Leaving	bed-Lying	sitting square	long sitting	standing outside	lying outside
bed-leaving	81.3 %	0.10 %	0.20 %	0 %	18.3 %	0.1 %
bed-lying	2.1 %	68.1 %	7.5 %	18.9 %	0.1 %	3.3 %
sitting square	0.2 %	23.7 %	56.6 %	4.3 %	4.6 %	10.6 %
long sitting	0.1 %	8.9 %	20.5 %	58.1 %	1.9 %	10.5 %
standing outside	0 %	0 %	6.4 %	0.9 %	86.4 %	6.3 %
lying outside	26.7 %	0.7 %	1.2 %	9.1 %	3.7 %	58.6 %

5. Conclusion

To develop practical remote bed monitoring systems for nursing care, this study aimed to classify various behaviors related to bed-leaving and bed-lying using short-term data generated via the received signals of 60 GHz millimeter-wave FMCW radar. The CNN, utilizing time-range images generated from radar data at 0.5 s intervals, achieved the accurate classification of bed-leaving and other representative behaviors (bed-lying, sitting square, long sitting, standing-out of the bed, and lying-outside of the bed). Even when we used the simple MobileNet, the detection rate of bed-leaving was 95.9%.In addition, we achieved the above six types of behaviors with 89.7% accuracy using the ResNet. However, the classification accuracy using the MobileNet was 68.5%, although it has merits in sufficiently smaller model size. Thus, to develop practical bed monitoring systems, future investigation to improve the classification accuracy using the multiple images of multiple receivers is required.

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