Radar-based Recognition of Activities of Daily Living in the Palliative Care Context Using Deep Learning

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***Abstract*—The accurate detection and quantification of activities of daily life are crucial for assessing the health status of palliative patients to allow an optimized treatment in the last phase of life. Current evaluation methods heavily rely on subjective self-reports or external observations by clinical staff, lacking objectivity. To address this limitation, we propose a radar-based approach for recognizing ADLs in a palliative care context. In our proof of concept study, we recorded five different activities of daily living relevant to palliative care, all occurring within a hospital bed, from N=14 healthy participants (57 % women, aged 28.6 ± 5.3 years). All movements were recorded using two frequency-modulated continuous wave radar systems measuring velocity, range, and angle. A convolutional neural network combined with long short-term memory achieved a classification accuracy of 99.8 ± 0.4 % across five cross-validation folds. Furthermore, we compare our initial approach, which takes into account all dimensions of the available radar data, to a simplified version, where only velocity information over time is fed into the network. While these results demonstrate the high potential of radar-based sensing to automatically detect and quantify activities in a palliative care context, future work is still necessary to assess the applicability to real-world hospital scenarios.**

***Index Terms*—activities of daily living, radar, deep learning, human activity recognition, palliative care**

I. Introduction

Palliative care is a specialized, interdisciplinary medical domain that provides support to individuals with various diseases, particularly cancer as well as cardiovascular, pulmonary, and neurological conditions. It aims at managing symptoms and improving patients' quality of life (QoL) in their remaining lifespan, rather than attempting to medically alter the course of the diseases [1]. In order to allow an optimized individual treatment, clinicians need to have the best possible knowledge about the current state of health, symptom burden, and lifetime prognosis. The health status of palliative patients is typically evaluated through self-reports or external assessment methods. In this regard, functional status and mobility play an important role. Validated instruments for the assessment are, for example, the Karnofsky index [2], a scale used to assess symptom-related limitations of activity, self-care, and self-determination in patients with malignant tumors. Another example is the Barthel index [3], which aims at measuring the performance of patients while performing activities of daily living (ADL) [4], that is routine self-care tasks that need to be performed to fulfill basic human needs [5]. However, as these established measures lack objectivity, they only allow a rough approximation of the current health status [6]. Therefore, a sensor-based and contactless assessment of ADL is desirable in a palliative care setting.

One approach to automatically assess ADL can be achieved by applying human activity recognition (HAR) techniques. In this context, different sensor types (and combinations) are used for data acquisition, while activities are automatically detected using machine learning (ML) techniques. In the HAR context, camera-based approaches have been researched intensively [7]. However, especially in the context of monitoring elderly individuals or patients in a hospital setting, the usage of cameras is limited due to privacy issues [8]. A promising alternative is provided by wearable sensor-based technologies. Previous work has successfully used accelerometers, together with classical ML or deep learning (DL) approaches, to track different patient activities, such as walking and standing within a simulated hospital environment or at home [9], [10]. However, these approaches require one or more accelerometers to be attached to or carried around the body. This imposes a substantial burden in the palliative care context, which is primarily focused on improving QoL in the last phase of life [1]. Consequently, radar technology has emerged as a promising contactless sensor for HAR in the healthcare context, as it protects the visual privacy of the people being captured. The radar-based fall detection of the elderly has especially been researched in this regard [11].

Prior research has shown that the use of radar sensors within palliative care is feasible and provides benefits over traditionally employed methods, as it enables contactless monitoring of vital signs with no impact on the QoL of patients [12]. In addition, the need for a contactless, sensor-based method to, first, detect and, second, quantify the ADLs of palliative patients, for example, regarding precision or speed, has been addressed by our prior work [13]. This also included exploratory radar data analysis, which demonstrated the great potential of radar technology in this context. Bhavanasi et al. [14] presented a radar-based HAR approach for 10 daily activities that take place in a hospital room environment. They make use of two radar systems that are placed at different locations in the room, each system measuring distance and

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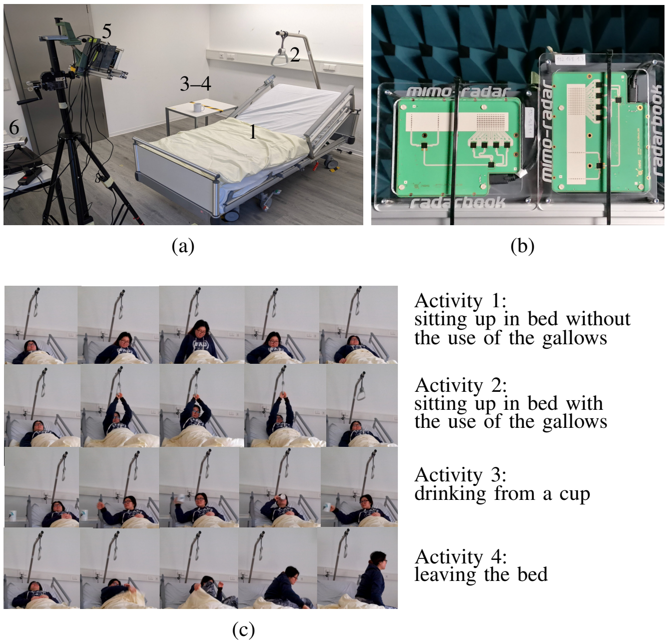


Fig. 1: Measurement setup. (a) Picture of the measurement setup including a hospital bed (1), a bed gallows (2), a desk with a cup (3–4), two radar systems mounted on a tripod (5), and an RGB camera (6). (b) Perpendicular arrangement of both FMCW MIMO radars. (c) Examples of activities 1–4 performed during the study (Activity 5 is not shown).

velocity. The activity recognition was then performed using deep convolutional neural networks (CNN). However, radar-based ADL recognition of palliative patients to allow an objective assessment of the functional status of patients has not been researched thus far.

For that reason, we present a proof of concept for radar-based detection of ADLs in the palliative environment and used a DL algorithm for automatic activity classification. We collected data from young healthy adults in a hospital bed performing basic ADLs that correspond to the ADL categories *ambulating* or *feeding* [5]. Therefore, this measurement setting as well as the ADLs considered are especially relevant for palliative care. We used two multiple-input multiple-output (MIMO) frequency-modulated continuous wave (FMCW) radar systems that measure distance, angle, and velocity. Based on these data, we trained a network structure consisting of a CNN and a long short-term memory (LSTM).

II. Methods

A. Measurement Setup

Our measurement setup consisted of one hospital bed with a tilted back support including a bed gallows, a desk with a cup on it, two identical FMCW radars (Radarbook2, INRAS GmbH, Linz, Austria) that form a one-dimensional MIMO array mounted on a tripod, a video camera, and a synchronization board (Fig. 1a). The radars were positioned at a height of 155 cm, and the line of sight was vertically tilted by 26°. The array dimensions of the radars were positioned perpendicular to each other (Fig. 1b).

B. Study Design

To assess the feasibility of radar-based ADL recognition in a hospital bed scenario, we collected data from 14 healthy participants (57 % women, aged 28.6 ± 5.3 years, height 171.9 ± 9.9 cm). The study was approved by FAU's ethics committee (protocol #468_20 B). Written informed consent was obtained from all participants prior to the study.

At the beginning of the study, participants were asked to lie down in the bed. Afterwards, we asked them to imitate five defined movements that are typically performed by patients in a hospital bed (Fig. 1c): sitting up in bed without (Activity 1) and with (Activity 2) the use of the bed gallows, drinking from a cup placed on the side table (Activity 3), leaving the bed (Activity 4), and turning over in bed (Activity 5). For activities 1 and 2 the starting position was defined by an unsupported lower back. The end position was a supported lower back due to the upper bed's tilt angle. Thus, we asked all participants to reposition themselves before starting activities 1 and 2, respectively. Activity 3 was defined by reaching toward the cup placed on the table, drinking from the cup, and placing the cup back on the table. Activity 4 consisted of removing the blanket from the legs and pushing the body towards the side of the bed.

We asked participants to perform each activity for at least five times before moving on to the next. The whole set of movements was repeated three times, leading to each activity being performed at least 15 times by each participant. All activities were in the same duration range (Activity 1: 4.5 ± 0.8 s; Activity 2: 5.7 ± 1.4 s; Activity 3: 8.9 ± 2.4 s; Activity 4: 6.8 ± 1.8 s; and Activity 5: 4.4 ± 1.3 s).

C. Radar Preprocessing

The MIMO FMCW radar systems used in our study operate at a center frequency of $f_0 = 77$ GHz with a bandwidth of $B = 2$ GHz. Each system consists of two sending antennas that send out sequences of frequency-modulated chirps (chirp duration $T_\mathrm{c} = 320\,\mu\mathrm{s}$, chirp repetition time $T_\mathrm{r} = 656\,\mu\mathrm{s}$). The chirps are received by each of the 16 receiving antennas to enable the simultaneous measurement of a target's velocity (Doppler), distance (range), and angle with respect to the radars' position. Furthermore, it allows the resolving of multiple targets in these dimensions [15]. The movement of a human body can thus be seen as a dense arrangement of moving targets that can be detected by the radar. Each radar sensor yields three-dimensional data where the dimensions describe antenna pairs, samples within one chirp, and chirps over time.

For preprocessing, we first segmented the continuous radar data stream into single movements using the time stamps collected during the study. Afterwards, we divided the data into multiple coherent processing intervals (CPIs) so that each measurement contained a fixed number of chirps ($N_\mathrm{c} = 152$)

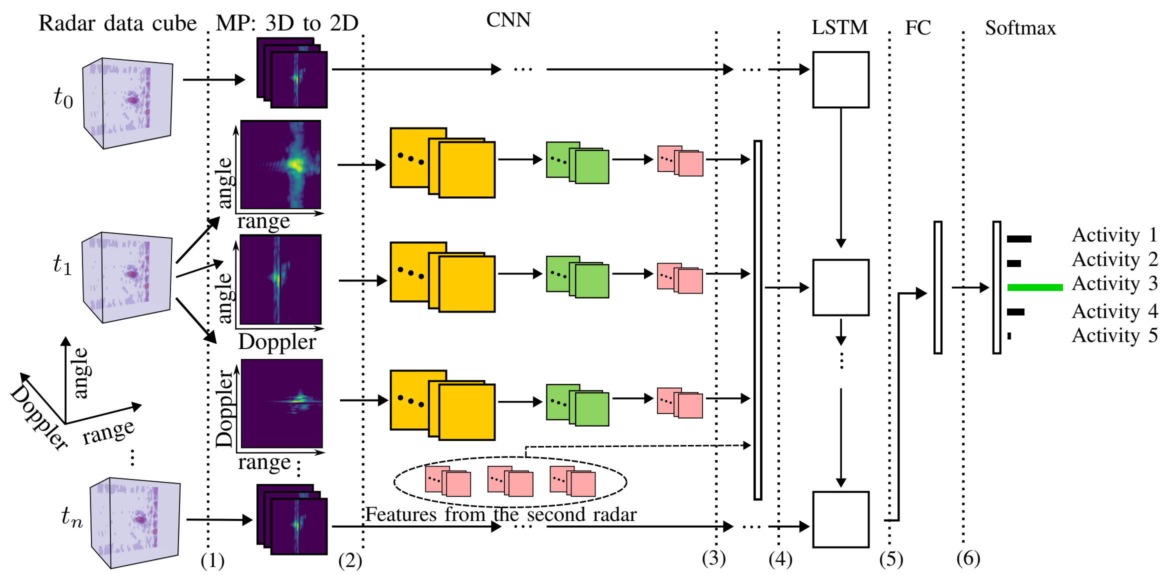


Fig. 2: Neural network architecture. (1) Projection of radar data cube of one time instance into three 2-d images. (2) CNN with three layers. (3) Flattening of CNN outputs of both radars and concatenation into a feature vector. (4) Many-to-one single-layer LSTM using the feature vector as input. (5) Fully connected layer. (6) Softmax activation function for calculating classification probabilities for each activity.

before applying a 3-d fast Fourier transform (FFT) on each CPI. This results in a 3-d tensor (also called *radar data cube*) which contains information about the velocity, range, and angle data of all targets within the object scene. The use of two perpendicular radar systems allows us to compute angular information from the horizontal (azimuth) and vertical (elevation) planes simultaneously.

After computing two radar data cubes (one for each radar system) per time step (CPI), we normalized the amplitudes to the maximum occurring amplitude within one movement and transferred them into a logarithmic scale. As the object scene included multiple static targets that caused strong reflections, we set the amplitude of all static targets to the minimum occurring amplitude. Furthermore, we limited the extension of the radar data cube to a range of 0.8–2.5 m, as well as azimuth and elevation angles between −60–60°. To reduce the dimensionality of our data, we performed a maximum intensity projection along each axis of both radar cubes individually, similar to the approach by Major et al. [16], where the authors summed up all FFT bins along each axis. This resulted in six 2-d representations: two range–Doppler images, two range–angle images, and two Doppler–angle images.

D. Classification of ADLs

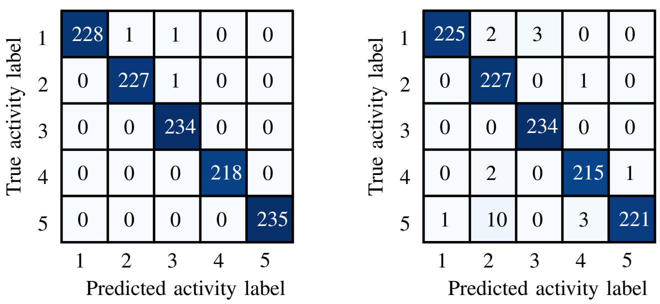
After preprocessing, we sequentially fed all six 2-d radar images obtained for each CPI into a neural network. It consisted of a CNN in combination with an LSTM (Fig. 2). Each 2-d image was convolved by an independent CNN with three 2-d convolutional layers with 16, 32, and 64 kernels, respectively. Each kernel had a size of 3x3. After each convolutional layer, we applied batch normalization, max-pooling of size 3x3 and stride 3, and a rectified linear unit (ReLU) layer. Afterwards, the outputs of the last convolutional layer of both radars were flattened and concatenated into one linear feature vector. This feature vector was then fed into a many-to-one single-layer LSTM with a hidden size of 128, followed by a fully connected layer. Finally, we applied the softmax activation function to calculate the classification probabilities for each activity. We optimized the model using a single validation set separated from the training set (80/20 split). For a defined number of epochs, we applied the validation set on the current model and calculated the corresponding loss. Each time a new minimum validation loss was found, we saved the model and finally evaluated the best model on the test set.

E. Evaluation

We evaluated our approach by performing a five-fold cross-validation (CV) that split our measurements into a training and a test set for each fold. The split between training and test data was 80 % to 20 %. In addition to the proposed approach using data from the entire radar data, we performed a second experiment where we only utilized Doppler information over time. This means the data from the azimuth radar were completely neglected and the data from the elevation radar cube were summed up along the range and angle axes. This approach is very similar to the frequently used spectrograms for activity recognition tasks [11].

III. Results

Since we asked participants to perform *at least* 15 repetitions for every motion, we obtained a total 1145 motion samples from all participants with the minimum number of samples for Activity 4 ($n = 218$). Our results yield an accuracy of 99.8 ± 0.4 % across all CV folds for our originally proposed approach using all dimensions of the radar data cube. The overall confusion matrix is visualized in Fig. 3a. Furthermore, we also evaluated the Doppler-only approach, which yielded an accuracy of $98.5 \pm 0.9\,\%$. The corresponding confusion matrix can be seen in Fig. 3b.



(a) (b)

Fig. 3: Confusion matrices for the classification using (a) range, Doppler, and angle, and (b) Doppler-only.

IV. Discussion

The results obtained from the study demonstrate the great potential of deep learning in combination with radar-based sensing for activity monitoring of palliative patients. The movements we selected for our study are representative of ADLs in this context. Nonetheless, it should be noted that the movements differ greatly in the dimensions of angle, velocity, and range over time (relative to the radar position). For instance, the *drinking* movement (Activity 3) inherits a characteristic motion in the azimuth's dimension, whereas the *sitting up in bed using the gallows* (Activity 2) is characterized by a motion in the elevation's dimension. During the *getting out of bed* movement (Activity 4), the range to the radar is reduced over time. Since the radar system used in this study is particularly designed to resolve changes along these dimensions, we expected our neural network architecture to reliably distinguish these activities. A reduction to only Doppler information over time yielded promising results, but a slight decrease in accuracy, which is mainly caused by misclassifying Activity 5 as Activity 2. However, the study solely focused on young, healthy individuals within a laboratory environment. Palliative patients may exhibit different movement patterns and physical limitations. Therefore, the speed and precision of motions might vary strongly over different patients, which is why a purely velocity-over-time-based DL approach might not be robust enough. Moreover, our study only monitored a set of five specific ADLs. This limited scope raises questions about the generalizability of our results to a broader range of movements commonly observed in palliative care settings. Furthermore, the method employed in the study involved manually cutting out movements from the continuous data stream. Therefore, plans for future research involve collecting a more diverse and representative data set and an automatic segmentation approach to allow a smooth transition of this proof of concept to real-world scenarios of palliative care.

V. Conclusion

In this paper, we presented a proof of concept for a radar- and DL-based recognition of ADLs in the hospital bed that are relevant in a palliative care setting. Our results show that the combination of two MIMO FMCW radar systems together with a neural network consisting of a multi-layer CNN together with an LSTM yields excellent recognition accuracy and demonstrates the great potential of our approach for an objective assessment of current health states of patients. In the future, we plan to evaluate our pipeline on data from actual palliative patients in the hospital. Furthermore, not only the detection of ADLs, but also the radar-based quantification of these regarding velocity and precision should be researched, as this is also of interest when assessing the current state of health of palliative patients.

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References

[1] C. Sepúlveda *et al.*, “Palliative care: The World Health organization's global perspective,” *J Pain Symptom Manage*, vol. 24, no. 2, pp. 91–96, 2002.

[2] D. Karnofsky, “The clinical evaluation of chemotherapeutic agents in cancer,” 1949.

[3] F. I. Mahoney and D. W. Barthel, “Functional evaluation: The Barthel Index,” *Md Med J*, vol. 14, pp. 61–65, 1965.

[4] The Staff of the Benjamin Rose Hospital, “Multidisciplinary studies of illness in aged persons. II. A new classification of functional status in activities of daily living,” *J. Chronic Dis.*, vol. 9, no. 1, pp. 55–62, 1959.

[5] Peter F. Edemekong *et al.*, “Activities of Daily Living,” in *StatPearls*, 2022.

[6] M. Baker *et al.*, “What do self-reported, objective, measures of health measure?” *J. Hum. Resour.*, no. 4, pp. 1067–1093, 2004.

[7] D. R. Beddiar *et al.*, “Vision-based human activity recognition: A survey,” *Multimed. Tools Appl.*, vol. 79, no. 41-42, pp. 30 509–30 555, 2020.

[8] Q. Ni *et al.*, “The elderly's independent living in smart homes: A characterization of activities and sensing infrastructure survey to facilitate services development,” *Sensors (Basel, Switzerland)*, vol. 15, no. 5, pp. 11 312–11 362, 2015.

[9] S. L. Lau *et al.*, “Supporting patient monitoring using activity recognition with a smartphone,” in *7th International Symposium on Wireless Communication Systems (ISWCS), 2010*, R. C. de Lamare, Ed. Piscataway, NJ: IEEE, 2010, pp. 810–814.

[10] E. Fridriksdottir and A. G. Bonomi, “Accelerometer-based human activity recognition for patient monitoring using a deep neural network,” *Sensors (Basel, Switzerland)*, vol. 20, no. 22, 2020.

[11] X. Li *et al.*, “A Survey of Deep Learning-Based Human Activity Recognition in Radar,” *Remote Sensing*, vol. 11, no. 9, p. 1068, 2019.

[12] K. Shi *et al.*, “A contactless system for continuous vital sign monitoring in palliative and intensive care,” in *The 12th Annual IEEE International Systems Conference*. Piscataway, NJ, USA: IEEE, 2018, pp. 1–8.

[13] “Abstracts from the 17th World Congress of the EAPC 2021,” *Palliative Medicine*, vol. 35, no. 1_suppl, pp. 1–243, 2021, abstract number: A-11.

[14] G. Bhavanasi *et al.*, “Patient activity recognition using radar sensors and machine learning,” *Neural Computing and Applications*, vol. 34, no. 18, pp. 16 033–16 048, 2022.

[15] X. Li *et al.*, “Signal processing for TDM MIMO FMCW millimeter-wave radar sensors,” *IEEE Access*, vol. 9, pp. 167 959–167 971, 2021.

[16] B. Major *et al.*, “Vehicle Detection With Automotive Radar Using Deep Learning on Range-Azimuth-Doppler Tensors,” in *2019 International Conference on Computer Vision workshops*. IEEE, 2019, pp. 924–932.