Monitoring Discrete Activities of Daily Living of Young and Older Adults Using 5.8 GHz Frequency Modulated Continuous Wave Radar and ResNet Algorithm

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Abstract. With numerous applications in distinct domains, especially healthcare, human activity detection is of utmost significance. The objective of this study is to monitor activities of daily living using the publicly available dataset recorded in nine different geometrical locations for ninety-nine volunteers including young and older adults (65+) using 5.8 GHz Frequency Modulated Continuous Wave (FMCW) radar. In this work, we experimented with discrete human activities, for instance, walking, sitting, standing, bending, and drinking, recorded for 10 s and 5 s. To detect the list of activities mentioned above, we obtained the Micro-Doppler signatures through Short-time Fourier transform using MATLAB tool and procured the spectrograms as images. The acquired data of the spectrograms are trained, validated, and tested exploiting a state-of-the-art deep learning approach known as Residual Neural Network

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(ResNet). Moreover, the confusion matrix, model loss, and classification accuracy are used as performance evaluation metrics for the trained ResNet model. The unique skip connection technique of ResNet minimises the overfitting and underfitting issue, consequently resulting accuracy rate up to 91%.

Keywords: Radar sensor · Non-invasive healthcare · Human activities identification · Deep learning · ResNet

1 Introduction

Activities of daily living (ADL) are essential and routine tasks that most healthy young and older adults can perform without assistance. The inability to perform these ADL might cause unsafe conditions and poor quality of life [1]. The healthcare team should be aware of the importance of assessing ADL in patients to help ensure that patients who require assistance and are identified [2]. Thus monitoring ADL is of utmost importance since any activity undetected can cause fatal injuries [3].

Recently, several sensing technologies have been implemented in this context to resolve these crucial issues and allow the identification of several human activities [4–12] or activities in order to detect critical events like falls [13–15]. Wearable sensors [16], thermal imaging [17], pressure sensors [18], and Radio Frequency (RF) sensors such as lightweight and low-cost radar schemes are among the technologies which can be effectively used for the identification of human activities [7,19,20]. To choose one or more technologies [20–24], we must analyze the benefits and drawbacks of each sensor when it comes to performance evaluation metrics like false alarms, model accuracy, proportion of failed identifications, cost, user compliance, and ease of deployment. Pressure and wearable sensors, for instance, have high detection accuracy, nevertheless, the gadget must be worn on the human's body, which can be uncomfortable at times, and the thermal imaging camera poses privacy issues. The radar sensor, on the other hand, provides an inexpensive, non-contact, and readily deployable solution for monitoring everyday activities [25].

This paper presents a deep learning-based solution utilizing Residual Neural Network (ResNet) for the identification of prevalent human activities like walking, sitting, standing, and other activities. To record human activities, we have used Frequency Modulated Continuous Wave (FMCW) radar exploiting Micro-Doppler (MD) signatures. Volunteers took part in the data collection process, which occurred in distinct locations. After data prepossessing, the deep learning model was trained to identify unknown human activities.

2 Methodology

2.1 Data Acquisition

We have used the dataset obtained for the recently finished project "Intelligent RF Sensing for Falls and Health Prediction - INSHEP" funded by Engineering and Physical Sciences Research Council (EPSRC). (http://researchdata.gla.ac.uk/848/) [26].

This dataset was recorded using an FMCW radar functioning at C-band (5.8 GHz) over a bandwidth of 400 MHz and an output power of +18 dBm. The radar was connected to an antenna with +17 dBm gain. A total of 99 volunteers took part in the experimental campaign, with an age range of 21 years to 99 years at 9 different and separate locations and data was recorded for 10 s (walking) and rest of the activities for 5 s with 3 repetitions for each activity. The received signal was used to generate MD signatures using Short-time Fourier transform. The typical radar working principle is shown in Fig. 1(a), where a radio frequency signal is transmitted and received when encountering any object within its range. Figure 1(b) depicts the typical waveform of FMCW radar. Every movement of the body produces a distinct MD signature that can be employed to distinguish between various everyday activities [27–29]. Fundamentally, FMCW radar is a kind of radar sensor that, like a basic continuous-wave radar, emits continuous transmission power. FMCW radar, unlike continuous-wave radar, can adjust its working frequency throughout the measurements.

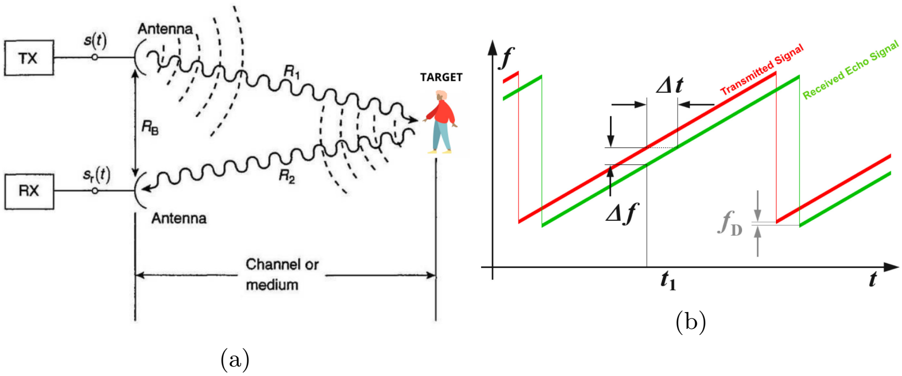


Fig. 1. (a) Typical radar working principle using reflected RF signal (b) FMCW radar waveform.

In this work, five distinct human activities were recorded using FMCW radar in separate locations, which were walking forward and back, sitting on a seat, standing from a seat, bending down to pick up an item, and drinking from a cup in standing position, as illustrated in Fig. 2 and listed in Table 1. Each human was asked to replicate the same task two or three times in order to collect data.

Figure 3 depicts the MD signatures of the data measurements. The spectrograms of a subject walking forward and back in front of radar are easily distinguishable from other activities. Activities like sitting on a seat and getting up from a seat are almost flipped images of each other. As shown in Fig. 3, when a subject bends down to pick up an item, the positive Doppler frequency changes significantly from 1.5–3 s. As the subject stood up again, a substantial alter in frequency was noted from 3.5–5 s.

Table 1. List of activities performed on humans.

Label	Activity
Activity 1	**Walking** (Forward and Back)
Activity 2	**Sitting** (On a Seat)
Activity 3	**Standing** (From a Seat)
Activity 4	**Bending** (Pick up Object)
Activity 5	**Drinking** (Standing Position)

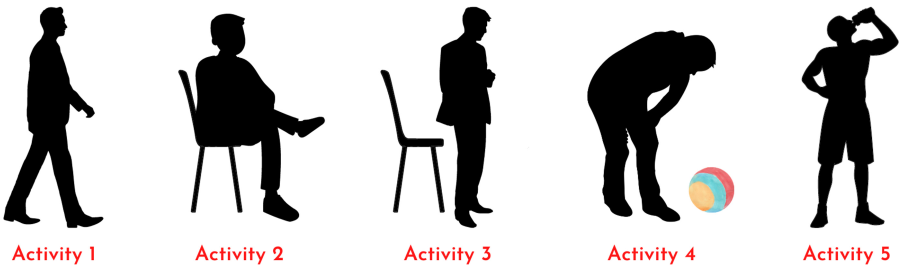


Fig. 2. Illustration of five distinct human activities. Activity 1 (Walking), Activity 2 (Sitting), Activity 3 (Standing), Activity 4 (Bending), Activity 5 (Drinking).

2.2 Classification Using Residual Neural Network

Machine learning-based techniques have been successfully employed in the past for different classification tasks [30–35]. In this paper, to classify distinct human activities through the obtained spectrograms, we have utilized a deep learning-based algorithm called Residual Neural Network or ResNet. The ability to train such a deep neural network (DNN) involves the use of skip connections. The input that feeds a layer is also applied to the output of a layer further up the stack. The aim of training a DNN is to get it to model a target function $h(x)$. If the network's output to the input is linked, for instance, adding a skip connection, the network would be strained to model $f(x) = h(x) - x$ instead of $h(x)$ [36,37]. This is referred to as "Residual Learning", as shown in Fig. 4.

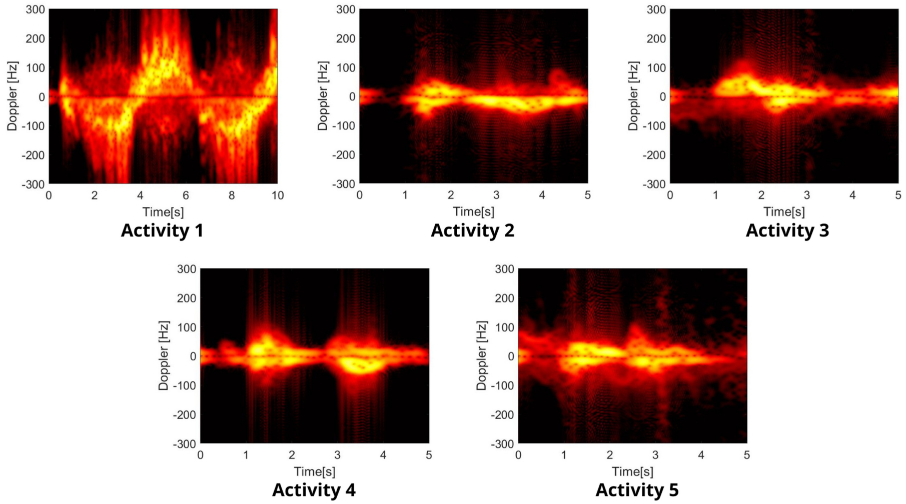


Fig. 3. Spectrograms of older adult with limited mobility - five different human activities.

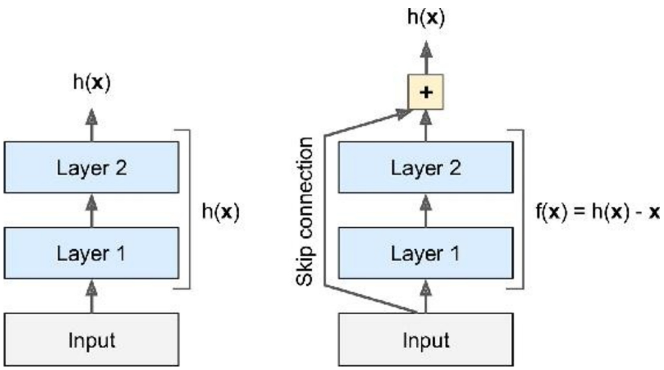


Fig. 4. ResNet learning framework.

The weights of a standard DNN are nearly zero when it is first initialised, so the network only outputs values near to zero. When a skip connection is added to the resulting network, it simply outputs a replica of its input, in other terms, it models the identity function at first. The training process can be significantly accelerated if the target function is close to the identity function which is frequently the case. Moreover, by adding a large number of skip connections, the network can begin to improve even though many layers are yet to learn. The signal can effectively traverse the whole network due to skip connections technique. The ResNet can be thought of as a pile of residual units, each of which is a diminutive neural network with a skip connection.

Furthermore, the establishment of a statistical relationship between the partial differential equation and the convolutional-residual-block assists to understand that why ResNet can be deeper to generate fine results in different tasks [38]. First, consider the following two-order partial differential equation:

$$\frac{\partial u(x,t)}{\partial t} = \frac{1}{2}\sigma^2 \frac{\partial^2 u(x,t)}{\partial x^2} + b\frac{\partial u(x,t)}{\partial x} + cu(x,t) \tag{1}$$

Equation 1 can be written in discrete form as:

$$\begin{aligned} &u(x,\ t+1) - u(x,\ t) = \tfrac{1}{2}\sigma^2(u(x+1,t) - 2u(x,t) + u(x-1,t)) + \tfrac{b}{2}(u(x+1,t) \\ &-u(x-1,t)) + cu(x,t) \end{aligned} \tag{2}$$

Equation 2 can be rewritten in convolutional form as:

$$u(x,\ t+1) = u(x,\ t) + \left[\tfrac{1}{2}\left(\sigma^2 + b\right), c - \sigma^2, \tfrac{1}{2}\left(\sigma^2 - b\right)\right] * u(x,t) \tag{3}$$

As regard to the convolutional-kernel as $w(x,t)$, Eq. 3 has the same structure as residual-block:

$$u(x,\ t+1) = u(x,\ t) + w(x,\ t) * u(x,\ t) \tag{4}$$

According to the results of the aforementioned analysis, any two-order partial differential equation could be altered as residual-block through a convolutional-kernel size of three, and any higher-order partial differential equation could be transformed to a residual-block through a greater convolutional-kernel. The residual-block and the two-order partial differential equation have a correspondence since the ResNet kernel size is normally minimal. Furthermore, the Fourier Transform is commonly utilized in the solution of partial differential equation, and it can help explain why, as previously mentioned, deeper ResNet contributes to better results. We get the following statistics by applying the Fourier Transform to Eq. 1:

$$\hat{T}_x = \frac{1}{2}\sigma^2\frac{\partial^2}{\partial x^2} + b\frac{\partial}{\partial x} + c \Longleftrightarrow \hat{T}_p = -\frac{1}{2}\sigma^2 p^2 + ibp + c \tag{5}$$

$$\hat{T}_p\tilde{u}(p,t) = \frac{\mathrm{d}}{\mathrm{dt}}\tilde{u}(p,t) \tag{6}$$

Solution of Eq. 6 is:

$$\tilde{u}(p,t) = e^{\hat{T}_p t}\tilde{u}(p,0) \tag{7}$$

If time t is minimal adequate, we get:

$$\tilde{u}(p,\ t) \approx \left(1 + \hat{T}_p t\right)\tilde{u}(p,0) \tag{8}$$

The following relationship can be obtained from the convolutional theorem by applying the inverse Fourier Transform to Eq. 8:

$$u(x,\ t) = u(x,0) + t\hat{T}_x\delta(x) * u(x,0) \tag{9}$$

Equations 4 and 9 are explicitly similar, and the convolutional-kernel $w(x,\ t)$ in continuous space corresponds to $t\hat{T}_x\delta(x)$. From a discrete point of view, Eq. 4 characterises the relation between the partial differential equation and the ResNet, while Eq. 9 captures the nature of the relation in the continuous domain. The numerals of the convolutional-kernels in residual-blocks are exceptionally minor. This is consistent with the fact that time t is short, since a short time span t means that the convolutional-kernel $t\hat{T}_x\delta(x)$ is mathematically small from Eq. 7–8. Furthermore, the lower size of the convolutional-kernels results in a low-order partial differential equation, which streamlines the iterative system's evolution. The analysis of the relation between the partial differential equation and residual-block provides insight into better comprehension of ResNet.

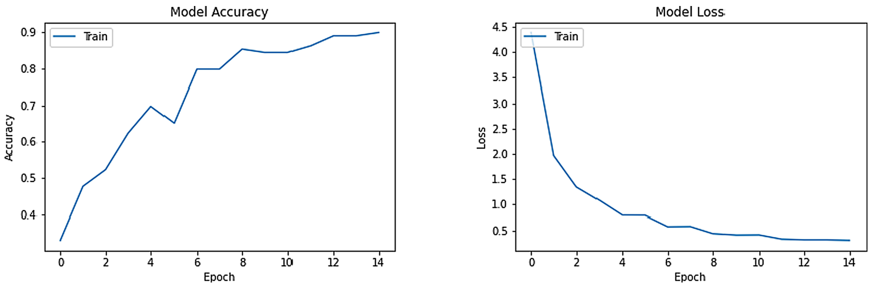
3 Results and Discussion

The ResNet algorithm considered in this study to identify distinct human activities was constructed in Python, primarily utilizing the TensorFlow and NumPy libraries. In this work, classification accuracy metric was taken into consideration to assess the performance of a trained model. The classification accuracy, in this case, human activity identification accuracy, can be described as the proportion of accurately identified human activities to the total number of human activities.

$$Identification\ Accuracy = \frac{Number\ of\ human\ activities\ identified}{Total\ number\ of\ human\ activities} \tag{10}$$

The dataset acquired consisted of five diverse human activities as listed in Table 1. Overall, 48×5 spectrograms were used for simulations, in which 22×5 were used for training, 4×5 for validation, and 22×5 for testing. Considering the size of a dataset, the number of epochs were set to 15 only and the DNN model ResNet was able to achieve accuracy up to 91%, as demonstrated in Fig. 5. Moreover, the model loss was recorded less than 0.5 as the number of epochs enhanced.

Additionally, Fig. 6 presents a confusion matrix of different human activities identified through the trained deep learning model. The ResNet was able to identify the walking activity with 100% accuracy. Moreover, there were only two misclassified instances for sitting and standing activities, hence exhibiting accuracy up to 90%. Whilst testing the trained model ResNet, the bending activity revealed maximum misclassified instances up to four against the drinking activity, therefore disclosing 81.8% accuracy. Lastly, the drinking activity unveiled 95% accuracy with only one misclassification against bending activity.



(a) (b)

Fig. 5. (a) ResNet model accuracy and (b) model loss against the number of epochs.

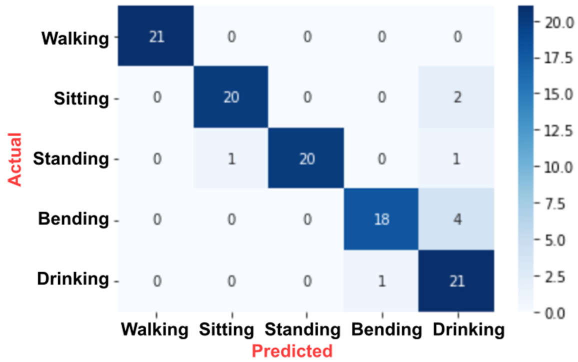


Fig. 6. Confusion matrix of five distinct human activities classified through ResNet.

4 Conclusions and Future Work

The idea behind this research is to exploit existing radar data to classify activities of daily living when data was obtained in nine different locations for ninety-nine volunteers. In this work, we provided preliminary findings for a simplified method that utilizes the FMCW radar to recognise distinct human activities such as walking, sitting, standing, bending, and drinking. As part of the experimental study, subjects were requested to undertake the five aforementioned human tasks at different geometrical positions. The radar system's MD signatures were then used as image data, and diverse features were extracted, validated, and trained using a well-known deep learning approach called ResNet. After training, the model was tested on various human activities spectrograms and simulation results revealed that ResNet attained up to 91% accuracy overall.

In the future, we aim to experiment with diverse diminutive human activities such as chest movement, lung movement, and minor gestures through hands or feet. Furthermore, we intend to utilize cutting-edge deep learning techniques such as Generative Adversarial Networks in order to regenerate lower acquired classes or instances from the datasets, hence increasing the performance of the trained algorithm.

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