

# Personal Hygiene Monitoring Under the Shower Using Wi-Fi Channel State Information

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## ABSTRACT

Personal hygiene is often used to measure functional independence, which is how much support someone requires to perform self-care. By extension, this is often used in the monitoring of (early-stage) dementia. Current technologies are based on either audiovisual or wearable technologies, both of which have practical limitations. The use of (NLOS) radio-frequency based human activity recognition could provide solutions here. This paper leverages the 802.11n channel state information to monitor different shower-related activities (e.g. washing head or body, brushing teeth, and dressing up) and the degree to which some of these can be monitored, as well as estimating different water pressures used while showering for multiple locations in the apartment. Wavelet denoising is applied for filtering and a convolutional neural network is implemented for classification. Results imply that for coarse-grained activity recognition, an  $F_1$ -score of 0.85 is achievable for certain classes, while for fine-grained this drops to 0.75. Water pressure estimation ranges from 0.75 to 0.85 between fine-grained and coarse-grained, respectively. Overall, this paper shows that channel state information can be successfully employed to monitor variations in different shower activities, as well as successfully estimating the water pressure in the shower.

## CCS CONCEPTS

• **Computer systems organization** → Sensor networks; • **Networks** → Wireless local area networks; • **Human-centered computing** → Ubiquitous and mobile computing.

## KEYWORDS

channel state information, human activity recognition, device-free sensing, 802.11n, personal hygiene, deep learning

## 1 INTRODUCTION

Personal hygiene is an important aspect in elderly care and even more so for those suffering from (early-stage) dementia. It is an important determinant of the level of support someone requires to perform self-care, which is part of the *functional independence in activities of daily living (ADL)* [1, 5, 6, 8, 15]. Most accepted solutions to monitor bathroom activities focus on the use of audiovisual

technologies [17], wearable technologies [9], or infrastructural sensors (e.g. pressure mats or door sensors) [2, 4, 18]. The audiovisual technologies cannot be placed in the shower as these are privacy-invasive. When it comes to wearable sensors, they may need to be taken off during shower time [9], unless they are waterproof. However, it cannot be assumed that elderly people and patients suffering from dementia never forget to wear a wearable device or know how to use properly use them. Lastly, infrastructural sensors often require great modification to existing homes (such as installing sensors in the ceiling, walls, and door frames) and these sensors are often bound to a specific location, whether that is a room or an object (such as a door frame).

Unlike the aforementioned technologies, radio frequency-based technologies (unobtrusive sensing) do not have to be put inside the shower itself, are more robust (e.g. do not need to be worn and cannot be forgotten) and are likely more privacy-aware, as the data is not easily interpretable by humans, since it requires more complex (pre)processing. This enables ADL monitoring [3, 16], abnormal activity detection [24], and vital sign monitoring [13, 21] using RF-based technologies. An activity often considered in health care, and even more so in elderly and dementia care, is falling [10, 14, 19, 22]. Falling is dangerous and happens most frequently in patient's rooms and bathrooms [11], with the actual room being ahead of the bathroom. However, falling in the bathroom often results in more serious injuries.

This paper leverages channel state information in a non line-of-sight (NLOS) environment to monitor the degree of shower behaviour on multiple locations in an apartment. This degree comes in the form of several shower-related activities, but performed in two different ways: one regular showering (as a person would), the other is by acting as if showering is troublesome (slow, painful, troublesome). Additionally, the activities of (un)dressing, drying of the body and brushing of the teeth are considered in their regular form. Results suggest that RF-based sensing can be used to investigate the aforementioned activities with an  $F_1$ -score score over 0.85, while also achieving a comparable  $F_1$ -score score for water pressure estimation, depending of the location of the receiver.

This paper first discusses the related works, which include works which inspired this research, as well as current solutions using other technologies. After that the data acquisition is discussed, as well as an overview of the dataset, to encourage fellow researcher to replicate this work and contribute to the presented dataset. During data acquisition, the variables are also discussed and how these are chosen. Following this, the actual methodology is discussed, which includes the ground truth evaluation, signal processing and data analysis. In the following Results and Discussion section, the actual outcome is evaluated and the research questions will be answered.

Finally, the paper concludes with a short summary of the results and suggestions for future work.

## 1.1 Challenges and contribution

Currently, little to no research has gone into personal hygiene detection under the shower, which is used in the monitoring of (early-stage) dementia. The use of audiovisual, wearable of infrastructural monitoring technologies has been proven [2, 4, 9, 17, 18], but come with downsides in privacy, installation and robustness. Most existing RF-based solutions focus either on detecting coarse-grained shower activities (such as washing or brushing teeth) and not on the degree to which these activities are performed.

The use of indirect (NLOS) radio-frequency based sensing could change this, as it reduced both the immediate privacy issues (video cameras under the shower) and the need for water-proof wearable devices and the wireless communication. Additionally, no infrastructural changes to a home are required, such as expensive shower heads, or tiles- and wall-mounted sensors. Due to the unobtrusive nature, RF-based sensing could prove to be useful in monitoring the variation to which shower activities are being performed, as well as combine these with shower information (e.g. water pressure). Multiple questions arise here in relation to the positioning of different receivers, but these will be discussed during the data acquisition and methodology.

The contributions of this paper are:

- To show the extend to which variations of different activities can be identified and monitored under the shower
- To show the extend to which different water pressures can be identified and monitored under the shower
- To investigate the effect of different receiver placement on the accuracy of the aforementioned aspects

## 2 RELATED WORKS

Channel state information is one of the most prominent RF-based sensing techniques. It gathers information regarding the signal multipath propagation between a transmitter and receiving antenna at the receiver side. Multipath propagation is a phenomenon caused by environmental influences on the signal, such as scattering, absorbing, and reflecting. These environmental influences include humans, and when monitoring the changes in the channel state information over time, the activities of them. Channel state information contains information on the phase and amplitude of the received signal. The combination of all these antenna pairs is collected in a channel state information matrix, which has the shape of  $N_r * N_t * N_s$ , where  $N_r$  is the number of receiving antennas,  $N_t$  the number of transmitting antennas, and  $N_s$  the number of subcarriers.

Research in activity recognition under the shower is fairly limited. Lee *et al.* [12] developed a system based on one transmitter and multiple receivers for activity recognition using 802.11n channel state information. As part of the research, different activities were considered, including bathing and toileting. It is shown that these activities can be detected with a high accuracy (higher than 95%) in two test beds when combining the receivers. However, fine-grained shower activity recognition and water pressure estimation are omitted. This paper will provide a deeper insight into different

water pressures and different gradations of performing the shower activities.

Zhang *et al.* [23] considered different poses in a bath using a single transmitter and receiver pair on the 5 GHz band: one regular (steady lying position) and two dangerous poses (the whole body sunk to the bottom and face-down in a bath). Data was collected by a single volunteer over the course of multiple months in a single apartment. Results show that an  $F_1$ -score of 89.47% can be achieved using this system. Zhang *et al.* considers the drowning dangers in a bath tub, but houses and especially smaller apartments often do not come with bath tubs. Therefore, this paper considers the shower to be another important source for personal hygiene and investigates the most prominent activities.

Wang *et al.* [20] developed *E-eyes* on the 5 GHz band with three off-the-shelf Wi-Fi devices connected to a single access point. The experiments are conducted in two apartments and the activities are performed by four male adults. Nine daily activities are considered, including bathing and brushing teeth, which were both performed in the bathroom. Wang *et al.* remark that the two activities have small differences in their CSI patterns [20, p. 8]. However, using wider-band signals, the false positive rate is lower than 1%. While this research does consider different (smaller) activities in the shower, it does not consider different receiver placement, water pressures, nor different degrees of the same activity.

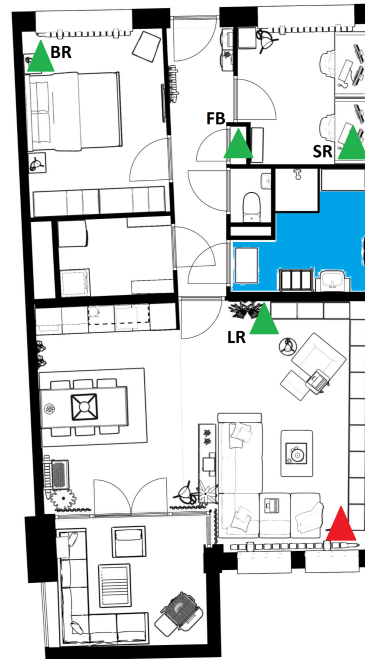


Figure 1: Apartment layout for the WiSh experiments. Green triangles represent the receivers, the red triangle represents the transmitter. The area in blue is the actual bathroom. Letters indicate both the location, as well as the identifier of the receiver, where LR=Living Room, FB=Fuse box, SR=Study Room, BR=Bed Room

### 3 DATA ACQUISITION

#### 3.1 Experimental setup

The setup consisted of a multiple custom Gigabyte Brix IoT devices, each consisting of an Intel Apollo Lake N34500 processor, 8GB DDRL 1866 MHz memory, and a n Intel N Ultimate Wi-Fi Link 5300 as a network interface. For these experiments, one functioned as a transmitter and the others as receivers. While the Linux CSI Tool [7] offers multiple options for connectivity, ultimately the injection mode was used. As for the frequency band, 5 GHz was used, as it is better capable in activity fine-grained activities due to its short wavelength ( $\lambda = 6.0cm$ ).

While multiple locations were considered for the transmitter, ultimately a setup was picked that consists of four receivers and a single transmitter (Figure 1). Here, the transmitter (red triangle) is located in the farthest corner from the apartment, where the actual Wi-Fi router would be located in this real-life setting. The first receiver is positioned in direct line-of-sight from the transmitter ( $\sim 7m$ ) as a zero-measurement (LR). The second receiver is placed in the fuse box compartment of the apartment (FB), positioning it skewed behind the shower ( $\sim 9.6m$ ), as it is close to the shower and the potential water pipes leading into it. The third receiver is located in the study room (SR), directly behind the the bath room. However, while the receiver is theoretically closer than receiver FB ( $\sim 8.5m$ ), the signal needs to propagate through more obstacles (e.g. walls and doors). The fourth and final receiver is placed in the bed (BR), which would theoretically result in the highest coverage (ignoring any obstruction). While it has the best propagation conditions (least overlap with the shower), it is the farthest away form the transmitter (13.9m).

It should be noted that the data was collected over multiple days, with the apartment being lived in regularly. This means furniture may be moved around and there could be slight changes to the position of the receivers. Overall, this setup is more relevant than a fixed laboratory setup, as it represents the actual use-case of such a system in the future. However, it was ensured no additional faucets (e.g. kitchen sink or dishwasher) were on while showering, as this was out of the scope for this research.

It is assumed that participants likely live alone or shower at times they are alone. However, it should be noted that there were two people in the apartment at all times during these experiments: the person not showering was always sitting at the kitchen table as far away as possible, minimizing the amount of movement on the signals. Cross-activity recognition among multiple people (e.g. one shower, one cooking) is not considered as part of this paper. Therefore, the the receiver in the living room is used to verify this has a minimum influence on the data collected by the other receivers. While concrete details on the participants cannot be given due to privacy concerns, it can disclosed that the two participants were a male and female, with a height difference of 15cm and a weight difference of 20kg. This shows the participants' physiques were not similar.

#### 3.2 Activities and water pressures

For this research, 9 activities are considered (Table 1). These activities are all based inside the bathroom, e.g. activities occurring under or around the shower in healthy participants and patients

**Table 1: List of all experimental parameters, including the activity abbreviations, where shower-related activities are in bold**

Parameter	Values	Count
Participants	0,1	2
Activities	Undress (UD), dry body (DB), <b>idle (I)</b> , <b>wash hair and face excitedly (WHF-E)</b> , <b>wash body and legs excitedly (WBL-E)</b> , <b>wash hair and face slowly (WHF-S)</b> , <b>wash body and legs slowly (WBL-S)</b> , brush teeth (BT), dress up (DU)	9
Water pressures	Off, low, med(ium), max(imum)	4
Receivers	LR,FB,SR,BR	4
<b>Total #combinations</b>		288

suffering from (early-stage) dementia. Therefore, some activities are not necessarily bound to showering (e.g. washing head/face), but also to other activities related to personal hygiene (e.g. brushing teeth).

All activities are considered with four different water pressures: off, low, medium, and high. It should be noted that these pressures can be minimized into a binary problem, namely *off* and *on* (low, medium, and high combined). It is likely that the water pressure is a personal preference, rather than there being a correlation between personal hygiene and the water pressure. Therefore, the binary problem of the shower being on or off is most prominent.

The activities under the shower are performed in two manners: one in a regular/excited fashion, the other in a slow/demotivated fashion. This is done to see if a differentiation can be made between either, in order to make it possible to monitor the degradation of personal hygiene in patients with (early-stage) dementia. For regular/excited, it is suggested the participants shower as they normally would, or in a very good mood. This could be different depending on the participant, as the definition of a very good mood and the results of such a mood differ per participant. For slow/demotivated, participants are asked to pretend like they are either physically restricted or in a very bad mood while showering.

Due to the sensitive of the data, no ground truth could be collected. Rather, participants are asked to follow a set of instructions (playing through a speaker in the shower) in order to have analogous activities in the same time slots. Between each activity is a moment for idling, which is used for both classification and to separate different activities.

No smart shower head was used, so the exact L/min is unknown and it is likely that per run, there is a slight difference between each. However, an attempt was made to replicate each shower based on the visual appearance and sound of the water beam coming out of the shower head. For *Low*, the shower should drizzle: barely any

water should come through the shower head. *Med* is the setting at which there is just enough pressure in the shower head to result in a consistent stream. The last setting, *Max*, requires the shower to be on at full force.

## 4 METHODOLOGY

### 4.1 Preprocessing

For preprocessing, the first step is restructuring of the channel state information, which is a 4D-matrix ( $3 * 3 * 30 * t$ ) due to 3x3 MIMO and 30 subcarriers over time  $t$ , into the shape of the input layer to the convolutional neural network, which has a shape of a 3D-matrix ( $H * W * D$ ). For these experiments, the data was flattened into a 3D-shape with a depth of 1 ( $D = 1$ ), namely  $270 * t * 1$ , as  $3 * 3 * 30 = 270$ . This means that for every antenna pair, the subcarriers are stacked on top of each other (e.g. the first 30 rows are receiving antenna 1 and transmitting antenna 1, the second 30 rows are receiving antenna 1 and transmitting antenna 2, and so on). Afterwards, wavelet denoising was used to denoise the signal in MATLAB, after which the data was stored as a set of images, where each pixels is thus based on an absolutely value for a specific subcarrier in a specific antenna-pair ( $H$ ) at time  $t$  ( $W$ ).

### 4.2 Classification

A convolutional neural network (CNN) is employed to for classification, as it preserves the spatial and structural information of the channel state information. The CNN consists of three 2D convolution layers, with a 0.6-dropout after the first and third layer. Max-pooling, batch normalization and a leaky ReLU ( $\alpha = 0.1$ ) for the activation layers are applied after each layer. At the end, the outputs are flattened and go through a 160-neuron dense layer with the sigmoid activation, before reaching the final dense layer for classification (softmax). The model was trained for 250 epochs, with a batch size of 8. The learning rate started with an initial learning rate of  $1 * 10^{-4}$ , with a decay rate of 0.95 every 50 steps. The split between the training and testing set used is 0.60 and 0.40 for the data of both users combined, respectively.

**4.2.1 Activity classification.** The first thing to consider is the activity classification in, regardless of the water pressure. For this, the shower-related activities (bold in Table 1) are combined over the different water pressures (including *Off*). This is to give an indication whether or not activity classification is affected by water pressure. A differentiation is made between all activities and shower-related activities, where all activities include activities only happening during *Off* and where shower-related activities only include those while the shower is on. This is evaluated over the different receiver locations.

**4.2.2 Water pressure estimation.** Here the labeling is based on the water pressure. All data is combined over the different activities depending on the water pressure. At the lowest level, the binary problem of shower *On/Off* is considered by clustering everything other than *Off* as *On*. Afterwards, this is turned into a more fine-grained problem where an attempt is made to differentiate per individual water pressure. For the classification of water pressure, only the shower-related activities are considered.

**4.2.3 Receiver positioning.** Finally, the activity classification and the water pressure estimation are compared between the different receivers (Figure 1). The most optimal location for these experiments will be discussed, as well as the worst performing one. For this, only the shower-related activities are used for both activity and water pressure recognition. Receiver LR is omitted, as it was used as a zero-measurement (no major movements happening in the living room).

BT	<b>1.0</b> $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$
DU	0.0 $\pm 0.0$	<b>1.0</b> $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$
DB	0.0 $\pm 0.0$	0.0 $\pm 0.0$	<b>1.0</b> $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$
I	0.13 $\pm 0.01$	0.0 $\pm 0.0$	0.00 $\pm 0.01$	<b>0.45</b> $\pm 0.16$	0.0 $\pm 0.0$	0.09 $\pm 0.07$	0.11 $\pm 0.11$	0.10 $\pm 0.07$	0.09 $\pm 0.10$
UD	<b>0.59</b> $\pm 0.18$	0.02 $\pm 0.05$	0.06 $\pm 0.12$	0.08 $\pm 0.14$	0.01 $\pm 0.05$	0.16 $\pm 0.21$	0.03 $\pm 0.05$	0.0 $\pm 0.0$	0.0 $\pm 0.0$
WBL-E	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	<b>0.91</b> $\pm 0.13$	0.08 $\pm 0.13$	0.0 $\pm 0.0$	0.0 $\pm 0.0$
WBL-S	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.01 $\pm 0.03$	0.0 $\pm 0.0$	0.18 $\pm 0.22$	<b>0.80</b> $\pm 0.24$	0.0 $\pm 0.0$	0.00 $\pm 0.00$
WHF-E	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.00 $\pm 0.02$	0.0 $\pm 0.0$	0.01 $\pm 0.02$	0.01 $\pm 0.01$	<b>0.93</b> $\pm 0.07$	0.03 $\pm 0.04$
WHF-S	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.0 $\pm 0.0$	0.02 $\pm 0.03$	0.0 $\pm 0.0$	0.05 $\pm 0.06$	0.03 $\pm 0.04$	0.11 $\pm 0.11$	<b>0.76</b> $\pm 0.17$
	BT	DU	DB	I	UD	WBL-E	WBL-S	WHF-E	WHF-S

(a)

**Figure 2: Classification of activities based on 10 runs with 250 epochs for  $p = \{0, 1\}$ ,  $n = SR$ , which includes all activities as mentioned in Table 1**

## 5 RESULTS AND DISCUSSION

### 5.1 Classification

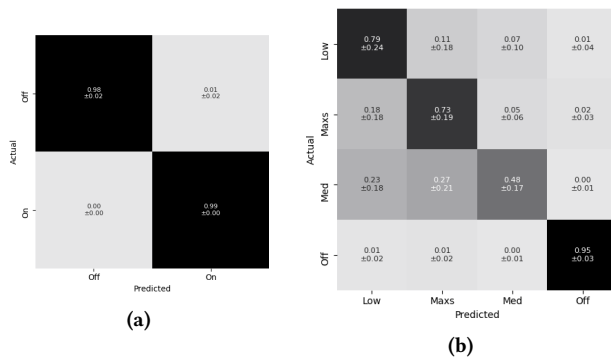
**5.1.1 Activity classification.** Figure 2 presents the classification as a confusion matrix for all activities for  $n = SR, p = 0$ , as all activities are important for the activity recognition part. While Figure 2 shows the normalized confusion matrix over 10 runs, the average  $F_1$ -score with standard deviation over these 10 runs are used as a metric when discussing specific classes. The overall  $F_1$ -score for all activities is  $0.74 \pm 0.05$ . For the case of all activities, 4 out of 9 classes have an  $F_1$ -score over 0.85 (*BT, DU, DB, WHF-E*) and 3 more an accuracy over 0.75 (*WHF-S, WBL-E/S*). The only exceptions here are idle (*I*)  $0.4 \pm 0.0$  and undress (*UD*), with an  $F_1$ -score of  $0.58 \pm 14$  and  $0.03 \pm 0.09$ , respectively.

For *undress*, this is likely due to the limited data, as the activity only lasts for 30 seconds. This causes only 40 data fragments after preprocessing. As a comparison, all other classes have at least 110 data fragments, with the showering activities (*WHF-E/S, WBL-E/S, I*) over 330. Additionally, undressing takes place at approximately the same location as brushing teeth.

For *Idle* it is a bit different, as it has a comparable number of data frames after preprocessing, namely 334 data frames. Idle is

mostly confused with brushing teeth ( $0.13 \pm 0.01$ ) and washing of the both the head and body (in the range of 0.11) for both slow and excited, likely due to these being activities involving minor body movements. Minor body movements are a part of idling, as participants cannot be expected to stand completely still in the shower (e.g. getting water in the eye or uncomfortable positioning).

Another observation is that there are darker squares in the confusion matrix around the two different performances (excited and slow) of *Washing body and legs* and *Washing hair and face*. For *Washing body and legs* and *Washing hair and face*, the  $F_1$ -score is  $0.77 \pm 0.15 - 0.81 \pm 0.07$  and  $0.80 \pm 0.10 - 0.87 \pm 0.07$ , respectively. The false-positives and true-negatives are in the range of 0.15, which is likely due to it being the same activity being performed with variation: sometimes an optimistic interpretation of slowly washing is close to a pessimistic interpretation of excited washing. Overall, this implies that an estimation can be made regarding the performance of washing, while there is a clearer distinction between washing the body and legs and washing the face. It is likely that the accuracy will drop when even more fine-grained activity recognition is considered (e.g. washing hair, face, upper body, and lower body).



**Figure 3: Classification of water pressure based on 10 runs with 250 epochs for  $p = \{0, 1\}$ ,  $n = SR$  for the washing and idling activities (*I,WHF-E/S,WBL-E/S*), where (a) is binary on/off and (b) identifies different water pressures.**

**5.1.2 Water pressure estimation.** Figure 3 shows the confusion matrices for the classification of the four water pressures for  $n = SR$ ,  $p = 0$ . Figure 3 includes the actual showering activities (such as idling and washing), namely *WHF-E*, *WHF-S*, *WBL-E*, *WBL-S*. Figures 3a,b are also normalized over the 10 runs.

For the binary problem of estimating whether the shower is on or off (Figure 3a), it is observable that this can be estimated with an  $F_1$ -score of  $0.99 \pm 0$  for the relevant activities (b).

For the individual shower pressures, the  $F_1$ -score of *Off* is  $0.97 \pm 0.02$  for classification with only the relevant activities. This is different for the other three: *Low* and *Max* have an  $F_1$ -score in the range of  $0.73 \pm 0.19 - 0.79 \pm 0.24$  for relevant activities, which is lower than for *Off*. This indicates that it is harder to differentiate between either. However, the lower  $F_1$ -score is largely explained by investigating *Med*, with a  $F_1$ -score of  $0.48 \pm 0.17$ : while *Low* and *Max* have false-positives and false-negatives between them, this is a minority compared to the false-positives and false-negatives

between the two and *Med*, as can be observed in the confusion matrices by the darker colors and upon further inspection of the actual classification rates. This indicates a larger difference between *Low* and *Max*, but lesser so between the two and *Med*, which can be explained by small differences in the shower sessions and the variation in the shower head: sometimes, medium may be exactly between low and maximum, but other times it may edge more towards either of the two.

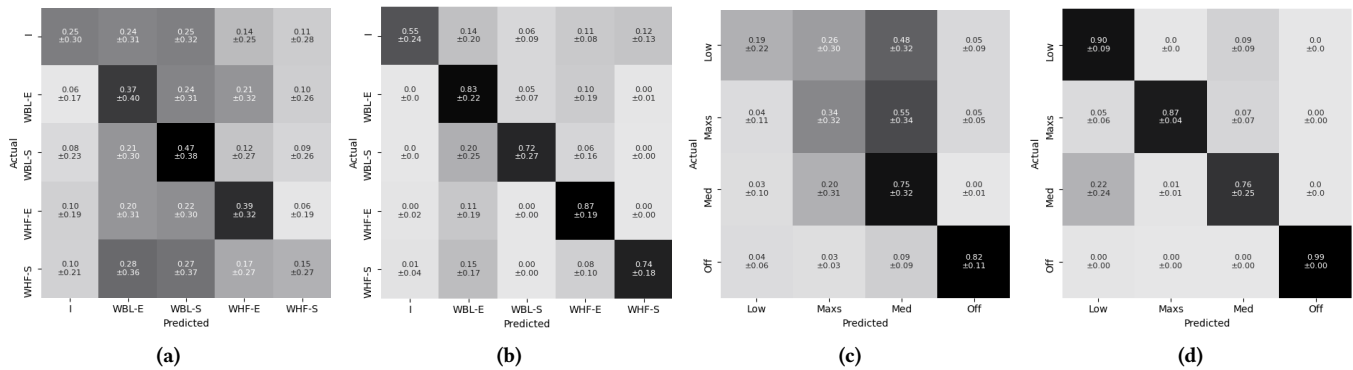
**5.1.3 Receiver positioning.** Figure 4 shows the additional classification performance for receivers FB (a,c), and BR (b,d). The top and bottom rows show the classification accuracy over 250 runs for  $p = \{0, 1\}$  for activities and water pressure recognition, respectively. The classification is based on the relevant activities, as these are the best case scenarios. The classification for all activities performs worse, as is previously discussed in sections 5.1.1 and 5.1.2. The information for receiver SR can be found in Figure 2 and 3 for activities and water pressure, respectively.

It can be seen that receiver SR is the most prominent at identifying the activities ( $F_1$ -score of  $0.74 \pm 0.05$ ), while receiver BR is most prominent at water pressure estimation ( $0.88 \pm 0.09$ ). While both score comparable on activity recognition ( $F_1$ -score of  $0.74 \pm 0.05$  and  $0.75 \pm 0.08$  SR and BR, respectively), BR has fewer classes that need classification (5 against 9 for bedroom and study, respectively), meaning the actual performance of BR is lower. Thus, these results imply that the bedroom is better for estimating the shower pressures, likely due to less noise from the water and pipes and thus the better signal propagation conditions, but that SR is better activity recognition, likely do to the path crossing the actual activities.

The worst performing receiver is FB, with an  $F_1$ -score of  $0.25 \pm 0.15$ ,  $0.90 \pm 0.01$ , and  $0.47 \pm 0.28$  for activity recognition, on/off, and individual water pressure estimation, respectively. The worse results could be explained by additional noise caused from the fuse box itself (more of interference from pipes running in and out), or that the most dominant signal is unaffected by the shower: from the transmitter to FB, it only needs to penetrate one door before it reaches the receiver, as the fuse box compartment is open at the top.

## 6 CONCLUSION AND FUTURE WORK

The results indicate that it is possible to determine whether the shower is on or off with an  $F_1$ -score of  $0.99 \pm 0.00$  and individual shower pressures with an  $F_1$ -score between  $0.48 \pm 0.17$  and  $0.79 \pm 0.24$  based over 10 runs. This implies that while it is challenging to detect certain individual shower pressures, it is feasible to monitor shower usage to a coarser degree. For activity recognition, an  $F_1$ -score of  $0.74 \pm 0.05$  on average is found. However, it is possible to differentiate between different levels (such as regular and slowed down movements) of shower-related activities (such as washing head or body) with an  $F_1$ -score of  $0.76 \pm 0.17$  and  $0.93 \pm 0.07$ . This indicates channel state information can be used to potentially monitor the personal hygiene for patients in self-care. Additionally, the results imply the optimal position to place the receiving receiver for the activity recognition is directly behind the shower, while for water pressure estimation it is recommended to put the receiver slightly skewed behind the shower for a more optimal propagation environment.



**Figure 4: Classification of activities and water pressure (10 runs, 250 epochs) for  $p = \{0, 1\}$  for receivers FB (a,c) and BR (b,d). (a) and (b) show the activity recognition for relevant activities, while (c) and (d) shows the water pressure estimation.**

Future work would include validating the results in this paper through more participants, different locations for the transmitter, and different frequencies. Repeating the experiments with more (and different) participants for different settings (e.g. multi-floor houses or larger apartments) is a must to verify these results in on a larger scale and for these technologies to be adapted into real-life scenarios. While 5 GHz has proven useful in this experiment, 2.4 GHz could be viable due to its larger wavelength, which means it is better capable at penetrating walls. Additionally, either frequency could also be affected by water in a different way. The proposed implementation should also be tested in a real-time for fashion for real-time classification.

## REFERENCES

- [1] Romola Bucks, D.L. Ashworth, G.K. Wilcock, and K Siegfried. 1996. Assessment of Activities of Daily Living in Dementia: Development of the Bristol Activities of Daily Living Scale. *Age and ageing* 25 (04 1996), 113–20. <https://doi.org/10.1093/ageing/25.2.113>
- [2] Mhd Daher, Ahmad Diab, Maan El Badaoui El Najjar, Mohamad Khalil, and François Charpillet. 2016. Elder Tracking and Fall Detection System Using Smart Tiles. *IEEE Sensors Journal* PP (11 2016), 1–1. <https://doi.org/10.1109/JSEN.2016.2625099>
- [3] Giovanni Diraco, Alessandro Leone, and P. Siciliano. 2017. A Radar-Based Smart Sensor for Unobtrusive Elderly Monitoring in Ambient Assisted Living Applications. *Biosensors* 7 (11 2017), 55. <https://doi.org/10.3390/bios7040055>
- [4] G. Feng, J. Mai, Z. Ban, X. Guo, and G. Wang. 2016. Floor Pressure Imaging for Fall Detection with Fiber-Optic Sensors. *IEEE Pervasive Computing* 15, 2 (2016), 40–47. <https://doi.org/10.1109/MPRV.2016.27>
- [5] Clarissa Giebel, Caroline Sutcliffe, and David Challis. 2014. Activities of Daily Living and quality of life across different stages of dementia: a UK study. *Ageing mental health* 19 (05 2014), 1–9. <https://doi.org/10.1080/13607863.2014.915920>
- [6] C.M. Giebel, C. Sutcliffe, M. Stolt, S. Karlsson, A. Renom-Guiteras, M. Soto, H. Verbeek, A. Zabalegui, the RightTimePlaceCare Consortium, and D. Challis. 2014. Deterioration of basic activities of daily living and their impact on quality of life across different cognitive stages of dementia: a European study. *International Psychogeriatrics* 26, 8 (1 Jan. 2014), 1283–1293. <https://doi.org/10.1017/S1041610214000775>
- [7] Daniel Halperin, Wenjun Hu, Anmol Sheth, and David Wetherall. 2011. Tool Release: Gathering 802.11n Traces with Channel State Information. *Computer Communication Review* 41 (01 2011), 53. <https://doi.org/10.1145/1925861.1925870>
- [8] S. Katz. 1983. Assessing self-maintenance: activities of daily living, mobility, and instrumental activities of daily living. *Journal of the American Geriatrics Society* (12 1983), 721–7. <https://doi.org/10.1111/j.1532-5415.1983.tb03391.x>
- [9] S. S. Khan, T. Zhu, B. Ye, A. Mihailidis, A. Iaboni, K. Newman, A. H. Wang, and L. S. Martin. 2017. DAAD: A Framework for Detecting Agitation and Aggression in People Living with Dementia Using a Novel Multi-modal Sensor Network. In *2017 IEEE International Conference on Data Mining Workshops (ICDMW)*. 703–710. <https://doi.org/10.1109/ICDMW.2017.98>
- [10] Jeroen Klein Brinke and Nirvana Meratnia. 2019. Scaling Activity Recognition Using Channel State Information Through Convolutional Neural Networks and Transfer Learning. 56–62. <https://doi.org/10.1145/3363347.3363362>
- [11] Melissa Krauss, Eileen Hitcho, Ngugi Kinyungu, William Dunagan, Irene Fischer, Stanley Birge, Shirley Johnson, Eileen Constantinou, and Victoria Fraser. 2005. A Case-Control Study of Patient, Medication, and Care-Related Risk Factors for Inpatient Falls. *Journal of general internal medicine* 20 (03 2005), 116–22. <https://doi.org/10.1111/j.1525-1497.2005.40171.x>
- [12] Hoonyong Lee, Changbum R. Ahn, and Nakjung Choi. 2020. Fine-grained occupant activity monitoring with Wi-Fi channel state information: Practical implementation of multiple receiver settings. *Advanced Engineering Informatics* 46 (2020), 101147. <https://doi.org/10.1016/j.aei.2020.101147>
- [13] J. Liu, Y. Chen, Y. Wang, X. Chen, J. Cheng, and J. Yang. 2018. Monitoring Vital Signs and Postures During Sleep Using Wi-Fi Signals. *IEEE Internet of Things Journal* 5, 3 (2018), 2071–2084. <https://doi.org/10.1109/JIOT.2018.2822818>
- [14] Sameera Palipana, David Rojas, Piyush Agrawal, and Dirk Pesch. 2018. FallDeFi: Ubiquitous Fall Detection Using Commodity Wi-Fi Devices. 1, 4 (2018). <https://doi.org/10.1145/3161183>
- [15] Ferris S.H. de Leon M.J. Crook T. Reisberg, B. 1982. The Global Deterioration Scale for assessment of primary degenerative dementia. *The American journal of psychiatry* (9 1982), 1136–9. <https://doi.org/10.1176/ajp.139.9.1136>
- [16] S. A. Shah and F. Fioranelli. 2019. RF Sensing Technologies for Assisted Daily Living in Healthcare: A Comprehensive Review. *IEEE Aerospace and Electronic Systems Magazine* 34, 11 (2019), 26–44. <https://doi.org/10.1109/MAES.2019.2933971>
- [17] Georgios Siantikos, Theodoros Giannakopoulos, and Stasinos Konstantopoulos. 2016. A Low-cost Approach for Detecting Activities of Daily Living using Audio Information: A Use Case on Bathroom Activity Monitoring. 26–32. <https://doi.org/10.5220/0005803700260032>
- [18] Reto Stucki, Prabitha Urwyler, Luca Rampa, René Müri, Urs Mosimann, and Tobias Nef. 2014. A Web-Based Non-Intrusive Ambient System to Measure and Classify Activities of Daily Living. *Journal of medical Internet research* 16 (07 2014), e175. <https://doi.org/10.2196/jmir.3465>
- [19] Wei Wang, Alex Liu, Muhammad Shahzad, Kang Ling, and Sanglu Lu. 2017. Device-Free Human Activity Recognition Using Commercial Wi-Fi Devices. *IEEE Journal on Selected Areas in Communications* PP (03 2017), 1–1. <https://doi.org/10.1109/JSAC.2017.2679658>
- [20] Yan Wang, Jian Liu, Yingying Chen, Marco Gruteser, Jie Yang, and Hongbo Liu. 2014. E-eyes: Device-free location-oriented activity identification using fine-grained Wi-Fi signatures. *Proceedings of the Annual International Conference on Mobile Computing and Networking, MOBICOM* (09 2014). <https://doi.org/10.1145/2639108.2639143>
- [21] Zhicheng Yang, Parth H. Pathak, Yunze Zeng, Xixi Liran, and Prasant Mohapatra. 2017. Vital Sign and Sleep Monitoring Using Millimeter Wave. 13, 2 (2017). <https://doi.org/10.1145/3051124>
- [22] Yue Zhang, Xiang Li, Shengjie Li, Jie Xiong, and Daqing Zhang. 2018. A Training-Free Contactless Human Vitality Monitoring Platform Using Commodity Wi-Fi Devices. 488–491. <https://doi.org/10.1145/3267305.3267613>
- [23] Zizheng Zhang, Shigemi Ishida, Shigeaki Tagashira, and Akira Fukuda. 2019. Danger-Pose Detection System Using Commodity Wi-Fi for Bathroom Monitoring. *Sensors* 19 (02 2019). <https://doi.org/10.3390/s19040884>
- [24] D. Zhu, N. Pang, G. Li, and S. Liu. 2017. Notifi: A ubiquitous Wi-Fi-based abnormal activity detection system. In *2017 International Joint Conference on Neural Networks (IJCNN)*. 1766–1773. <https://doi.org/10.1109/IJCNN.2017.7966064>