RF-Based Device-Free Recognition of Simultaneously Conducted Activities

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Abstract
We investigate the use of received RF-signals for activity recognition in scenarios with multiple receive nodes and multiple simultaneously active individuals. Our system features a short 0.5 second window over which features are calculated and we report on experiences in the choice of the neighbourhood size of the k-nearest neighbour (k-NN) classifier utilised. In a case study with software defined radio nodes utilised in an active, device-free activity recognition (DFAR) system, we observe a good recognition accuracy for the recognition of multiple simultaneously conducted activities with two and more receive devices. This is the first study to distinguish this particular set of activities from users conducting them simultaneously. For a single individual, we repeat the experiment and report the recognition accuracy in scenarios where the recognition area per receive node is larger than 8m^2.

Author Keywords
Environmental sensing, Device-free activity recognition

ACM Classification Keywords
J.9.d [Pervasive computing]: .; H.5.5.c [Signal analysis, synthesis, and processing]: .; I.5.4.m [Signal processing]: .

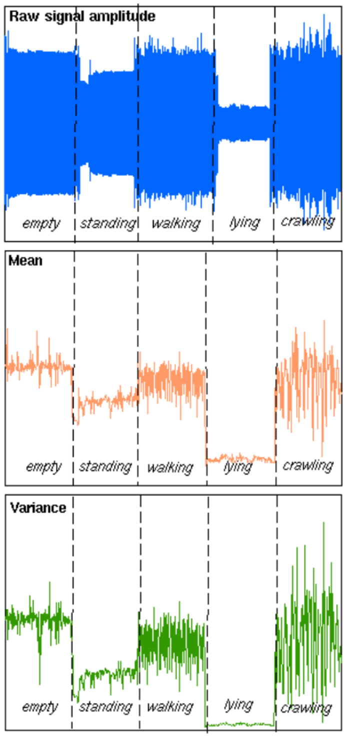

Figure 1: Evolution of the amplitude, its mean and variance of a received signal while various activities are conducted

Introduction

Recently, the use of received RF-signals for the localisation of entities or the recognition of activities from passive individuals has been investigated by various authors. These systems take advantage of the fluctuation in the RF-signal strength induced by individuals in proximity of a receiver blocking or reflecting signal propagation paths [7].

While the localisation of individuals has received much attention (see [12] and references therein), current work is shifting to other domains such as the counting of multiple subjects [11], the sensing of traffic situations [2, 3], or the distinction of activities [10, 9, 4]. In previous studies, in particular in active systems that incorporate a transmitter as part of the system, typically a single receiver and a single individual conducting activities at a time are investigated.

At the time of writing on the final version of this document, another study reporting an the simultaneous detection of gestures from multiple individuals was accepted for publication [6]. However, the authors utilise another approach that requires multiple antenna receive nodes and the analysis of micro Doppler fluctuations.

In this study, we investigate the yet untackled but relevant possibility of device-free sensing of activities conducted by multiple persons simultaneously from single-antenna receive devices. Furthermore, we consider the impact of multiple receive devices and a large recognition area covered by a single sensor. We employ USRP[1] software defined radio (SDR) devices placed in an environment for an active device-free activity recognition system.

Recognition of activities from RF fluctuation

We are exposed to signals at multiple frequency bands continuously and virtually everywhere. These signals are damped, blocked, reflected and scattered at objects before their superimposition reaches a receive antenna on multiple paths. Movement of individuals in proximity to this antenna therefore induces patterns on the evolution of the RF-signals which can be used to classify situations, locations or activities [12, 3, 10]. Figure 1 depicts this impact on the signal and feature evolution of a received signal by a single receiver while a person in proximity conducts various activities. Already simple features such as the mean or variance of the amplitude show characteristic patterns for distinct activities. In this study, we utilise the count of signal peaks within 10% of the maximum, the mean difference between subsequent maxima, the count of zero crossings, the variance and the mean as features to classify activities (cf. figure 2). This set of features is the result of a feature selection and manual feature reduction we conducted on a total of 17 features and their pair-wise combination.

Case Studies

We deploy five USRP SDR devices in a fully equipped indoor environment (a meeting room of about 8m×6m) to cover a recognition area of about 5.5m×1.5m (cf. figure 3). One of the devices is constantly transmitting a 2kHz sine signal, sampled at 320k and modulated onto a wireless carrier at 900MHz. For the recognition of activities, we utilise samples at 40Hz from the received sine signal and analyse the evolution of the signal strength at the receive device.

[1]http://www.ettus.com

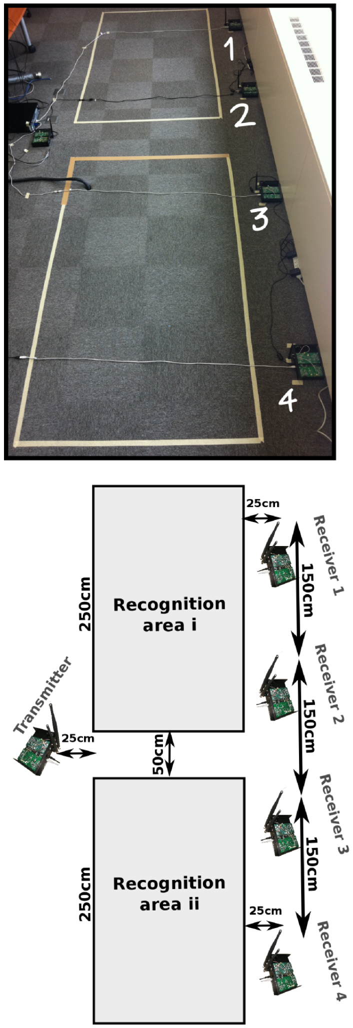

Figure 3: Schematic of the case study. For classification, different configurations of 1, 2, 3 or all receivers are utilised.

Assume that $|\mathcal{W}_t|$ samples s_i are taken on the signal strenth of an incoming signal for a window $\mathcal{W}_t = s_1^t, \ldots, s_{|\mathcal{W}_t|}^t$

Mean signal strength

The mean signal strength over a window of measurements represents static characteristic changes in the received signal strength.

It provides means to distinguish a standing person as well as her approximate location.

$$\mathsf{Mean}(\mathcal{W}_t) = \frac{\sum_{s_i \in \mathcal{W}_t} s_i}{|\mathcal{W}_t|}$$

Variance of the signal's strength

The variance of the signal strength represents the volatility of the received signal.

It can provide some estimation on changes in a receiver's proximity such as movement of individuals

$$\mathsf{Var}(\mathcal{W}_t) = \sqrt{\frac{\sum_{s_i \in \mathcal{W}_t} (s_i - \mathsf{Mean}(\mathcal{W}_t))^2}{|\mathcal{W}_t|}}$$

Count of zero crossings

The count of zero crossings over a sample interval is a measure of the fluctuation in a received signal's strength.

It can be leveraged in order to estimate the count of individuals or movement in proximity of a receiver.

$$g(s_i) = \begin{cases} 0 & \text{if } \mathsf{sgn}(s_{i-1}) = \mathsf{sgn}(s_i) \\ 1 & \text{else} \end{cases}$$

$$\mathsf{ZeroCross}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} g(s_i)$$

Signal peaks within 10% of a maximum

Reflections at nearby or remote objects impact the signal strength at a receive antenna. When all peaks are of the similar magnitude, this is an indication that movement is farther away.

This feature can indicate near-far relations and activity of individuals.

$$h(s_i) = \begin{cases} 1 & \text{if } s_i \geq \max(s_1, \ldots, s_{|\mathcal{W}|}) \cdot 0.9 \\ 0 & \text{else} \end{cases}$$

$$\mathsf{max}_{0.9}(\mathcal{W}_t) = \sum_{s_i \in \mathcal{W}_t} h(s_i)$$

Mean difference between subsequent maxima

When the maximum peaks within a sample window are of similar magnitude, this indicates low activity in an environment or static activities. The opposite might be found with dynamic activities

$$\mathcal{W}_{\max}(\mathcal{W}_t) = \{s_i \mid s_i \in \mathcal{W}_t, s_{i-1} < s_i \wedge s_i > s_{i+1}\}$$

$$a(\mathcal{W}_t) = \sum_{\substack{\forall s_i, s_j \in \mathcal{W}_{\max}(\mathcal{W}_t); \\ i<j; \\ \nexists s_k \text{with} i<k<j}} \frac{|s_i - s_j|}{|\mathcal{W}_{\max}(\mathcal{W}_t)|}$$

Figure 2: Features utilised for classification of activities

In the environment, two recognition areas are marked in which the activities 'walking', 'crawling', 'lying' or 'standing' are performed by two individuals simultaneously. In conformance with our previous studies, we placed the SDR devices on the floor in order to retain comparability. For the detection we considered a single, two, three or four receive devices in various constellations (see figure 3). Note that symmetrical constellations (e.g. receiver 1 and receiver 2 vs. receiver 3 and receiver 4) are omitted. The above parameters and activities have been chosen in accordance with previous studies (cf. [10]) in order to be comparable to preceding experiments. Each activity is conducted by both individuals alone and together in all possible combinations for at least three minutes. Feature values are calculated over a window of 500 milliseconds each. Consequently, for each activity and each feature, about 360 samples are created. The classification is done by a k-NN classifier.[2] The neighbourhood size k of this classifier was decided as a result of an investigation on the features acquired. An optimal choice is dependent on the count of receive devices or features utilised. Since each receiver produces RF signal strength data from which we extract six features each, the total count of features is correlated to the number of receive devices and a multiple of 6. With higher dimensional feature spaces, individual samples are more distinctive so that fewer neighbours (k) are required to train the classifier (cf. figure 4 for the impact of an increasing value of k).

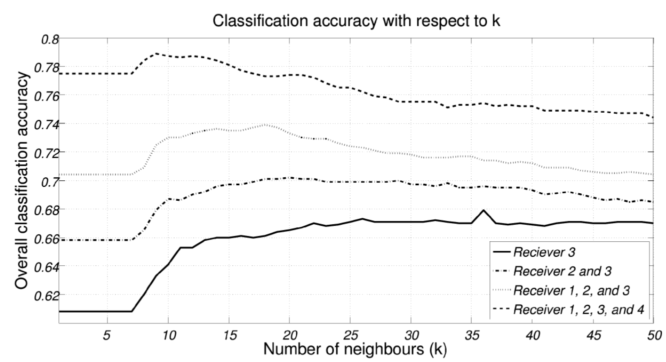

Figure 4: Overall accuracy for simultaneously performed activities when a single individual is conducting activities in both recognition areas

[2]We have also experimented with a naive Bayes and a decision tree classifier. However, the k-NN classifier was able to derive best classification results in most cases.

Ground truth	cr	em	ly	st	wa
cr	**.574**	.150	.003	.081	.192
em	.011	**.928**	.003	.017	.042
ly			**1.0**		
st	.017	.045	.003	**.877**	.058
wa	.114	.237	.003	.092	**.554**

(a) Confusion Matrix (R 1,2,3)

Ground truth	cr	em	ly	st	wa
cr	**.643**	.139	.019	.042	.156
em	.025	**.861**	.003	.061	.05
ly			**1.0**		
st	.028	.170	.008	**.733**	.061
wa	.117	.209	.019	.123	**.532**

(b) Confusion Matrix (R 1,2,4)

Table 1: Classification accuracy with three receive devices.

Ground truth	cr	em	ly	st	wa
cr	**.760**	.095	.003	.017	.125
em	.019	**.916**		.025	.039
ly			**1.0**		
st	.022	.056	.006	**.866**	.05
wa	.089	.198	.006	.061	**.646**

Table 2: Classification accuracy with four receive devices

The figure shows the overall classification accuracy of the k-NN classifier utilising exemplary feature data from 1, 2, 3 or 4 distinct receive devices. We observe that the classification accuracy increases with rising number of receive devices utilised and, simultaneously the optimum value of k is decreasing. With the addition of each further receiver, the overall classification accuracy is increased by about 0.05. Clearly, the optimum choice of k is dependent on the count $\mathcal{F}$ of features utilised and the number of classes $\mathcal{C}$ to distinguish between. In our case, the optimum value of k over all 22 case studies conducted was approximately

$$k = (50 \log \mathcal{F}) - \mathcal{C}.$$

In order to allow for a better comparison, we keep the neighbourhood size k of the k-NN classifier fixed over a set of case studies. For the detection of activities from a single individual, we fix k at $k = 10$. For the simultaneous detection of activities from two individuals we choose $k = 20$. These are conservative choices in order to reach acceptable results over all cases considered. Results are presented after 10-fold cross-validation.

Single individual

For comparison with previously conducted studies, we considered the recognition of a single individual in the environment depicted in figure 3. However, note that the window over which the features are calculated is with 500 ms considerably shorter than the windows chosen in the literature on RF-based device-free activity recognition. This shorter window allows the design of a more responsive system. We show that the classification accuracy is still sufficiently high. A single subject is performing the activities anywhere in the 5.5m×1.5m region spanned by recognition areas i and ii. Table 3 details the recognition accuracy achieved by a single receive device. The accuracy is comparable to previous results achieved in the literature and best when one of the central receive devices (receiver 2 or 3) is utilised. When receiver 1 and 4 are chosen, part of the activities are performed in more than 5m distance. Under these unfavourable conditions, the classification accuracy further drops. The hardest distinction for the recognition system is observed between the dynamic activities crawling and walking. Since for both classes a specific signal amplitude together with its frequent fluctuation is characteristic, activities conducted near and far from a receiver are easily confused. Clearly, by considering multiple receive devices, the recognition accuracy can be boosted (cf. table 5 for the classification accuracy, IS, Brier and AUC scores for several cases). Still, a confusion between dynamic activities can be observed.

Ground truth	cr	em	ly	st	wa
cr	**.368**	.134	.097	.136	.265
em	.064	**.802**	.008	.036	.089
ly	.031		**.953**	.006	.011
st	.064	.064	.025	**.749**	.097
wa	.256	.203	.045	.162	**.334**

(a) Confusion matrix (Rec. 1)

Ground truth	cr	em	ly	st	wa
cr	**.426**	.159	.061	.097	.256
em	.070	**.685**	.008	.061	.175
ly	.006		**.981**	.008	.006
st	.047	.042	.042	**.802**	.067
wa	.281	.287	.033	.134	**.265**

(b) Confusion matrix (Rec. 2)

Ground truth	cr	em	ly	st	wa
cr	**.362**	.234	.028	.106	.270
em	.072	**.772**	.003	.025	.128
ly			**1.0**		
st	.078	.006	.003	**.855**	.058
wa	.212	.214		.128	**.446**

(c) Confusion matrix (Rec. 3)

Ground truth	cr	em	ly	st	wa
cr	**.493**	.175	.07	.056	.206
em	.128	**.674**		.075	.123
ly	.008		**.989**		.003
st	.047	.100	.003	**.788**	.061
wa	.242	.198	.036	.039	**.485**

(d) Confusion matrix (Rec. 4)

Table 3: Classification accuracy for five basic activities while different receive devices are utilised (one receiver each).

Ground truth	cr	em	ly	st	wa
cr	**.482**	.145	.033	.089	.251
em	.036	**.794**		.07	.1
ly	.006		**.983**	.003	.008
st	.042	.075	.028	**.774**	.081
wa	.159	.256	.011	.120	**.454**

(a) Confusion matrix(R1 and 2)

Ground truth	cr	em	ly	st	wa
cr	**.521**	.145	.017	.084	.234
em	.033	**.841**		.033	.092
ly			**1.0**		
st	.019	.036	.011	**.894**	.039
wa	.195	.234	.003	.081	**.487**

(b) Confusion matrix(R1 and 3)

Ground truth	cr	em	ly	st	wa
cr	**.574**	.136	.033	.072	.184
em	.031	**.852**		.061	.056
ly	.003		**.994**	.003	
st	.045	.142	.011	**.733**	.07
wa	.195	.192	.017	.120	**.476**

(c) Confusion matrix(R1 and 4)

Ground truth	cr	em	ly	st	wa
cr	**.471**	.201	.014	.109	.206
em	.045	**.797**	.003	.017	.139
ly			**.997**	.003	
st	.033	.025	.008	**.897**	.036
wa	.145	.251	.006	.109	**.49**

(d) Confusion matrix(R2 and 3)

Table 4: Classification accuracy of five basic activities while different receive devices are utilised (two receivers each).

For instance, table 4 depicts the situation observed for two receive nodes.

In the cases with three or four receive nodes (cf. table 1 and table 2) this issue with the dynamic activities was weakened but not completely mitigated.

	Constellation of receive devices						
	1,2	1,3	1,4	2,3	1,2,3	1,2,4	1,2,3,4
CA	.697	.749	.726	.730	.787	.754	.838
IS	1.49	1.64	1.57	1.57	1.7	1.65	1.86
Brier	.421	.355	.388	.390	.318	.343	.229
AUC	.930	.946	.939	.928	.958	.960	.980

Table 5: Overall performance of the k-NN classifier

Multiple individuals

In all previous work on RF-based activity recognition, the activities of only a single subject were considered. Further subjects in proximity will, however, likely blur the pattern observed in the received signal for the activity recognition. In the scenario depicted in figure 3, we consider the simultaneous detection of activities from two subjects. For this case study, the individuals co-performed each combination of the five cases 'walking' (w), 'crawling' (c), 'standing' (s), 'lying' (l) and 'empty' (e) in the two recognition areas. Activities have been conducted by two individuals while each combination of activities was performed for at least three minutes. For the classification, features are chosen identical to the above consideration for a single individual (cf. figure**link to feature box**). Results are presented after 10-fold cross validation on a k-NN classifier with $k = 20$. Figure 5 depicts the confusion matrix when all four receive devices are utilised.

We label the 25 different cases performed in the notation 'activity in recognition area i'-'activity in recognition area ii'. For instance, when the subject in recognition area i is performing the activity walking while the subject in recognition area ii is crawling, the label of this joint activity would be w-c.

For ease of presentation, entries that were not observed (0.0 in the confusion matrix) are omitted. From the confusion matrix, we can again observe that the dynamic activities crawling and walking are frequently misclassified as the respective other activity.

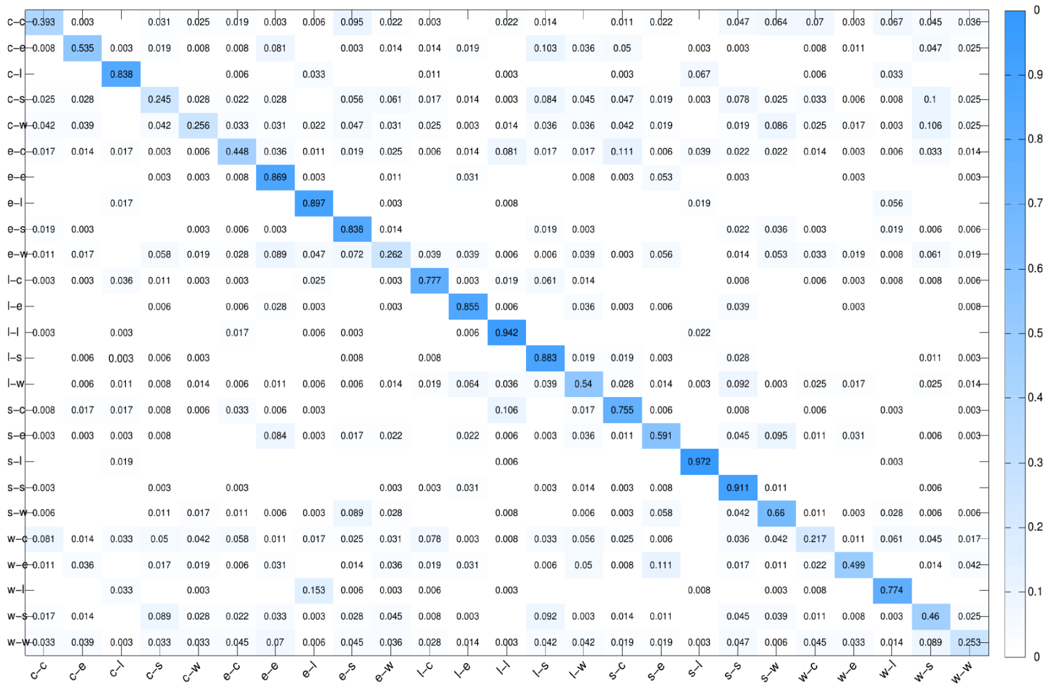

Figure 5: Accuracy for simultaneously performed activities

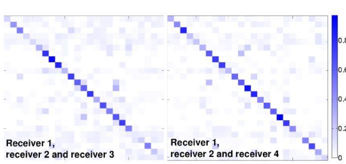

Figure 6: Confusion matrix with three receive nodes

Furthermore, the least errors are observed when solely static activities such as standing, lying or walking are conducted. Possibly, by utilising a multi stage classifier (similar to [8]) which fist distinguishes between dynamic or static activities, the accuracy can be further improved. However, overall we observe that, even though the activities are co-performed, most combinations are well distinguished. However, we utilised all four receive devices to achieve this result. With fewer receivers the accuracy drops as depicted in figure 7. The figure depicts the mean accuracy achieved over all considered constellations covering three receive devices. First, we observe that there are fewer entries with 0.0 in this confusion matrix. Also, the overall accuracy drops.

In addition, the observed lower accuracy for dynamic activities can also be observed for this case with three receive nodes. Generally, a slightly better accuracy was observed when receive nodes were farther spread, covering receiver 1 and receiver 4 (cf. figure 6)

This can also be observed from table 6. The table depicts the overall classification accuracy, IS, Brier and AUC scores for various constellations of receive devices. Furthermore, the table shows that the overall classification accuracy generally drops with fewer receive nodes.

	Constellation of receive devices						
	1,2	1,3	1,4	2,3	1,2,3	1,2,4	1,2,3,4
CA	.246	.418	.516	.26	.425	.52	.627
IS	1.537	2.25	2.693	1.598	2.288	2.732	3.112
Brier	.909	.745	.639	.894	.0737	.628	.51
AUC	.845	.917	.949	.859	.927	.96	.976

Table 6: Overall performance of the k-NN classifier when two subjects perform activities simultaneously

We can see this again for the combination of the confusion matrices for all constellations with two receive nodes (see figure 9). We observe that there are no entries with 0.0. Furthermore, the overall accuracy drops considerably. Again, the location of receive devices utilised impacts the classification accuracy.

We could observe a better accuracy when receive devices are further spread (cf. figure 8). In particular, in the figure, we observe that the overall confusion of classification is lower when receive devices 1 and 4 or receiver 1 and receiver 3 are combined.

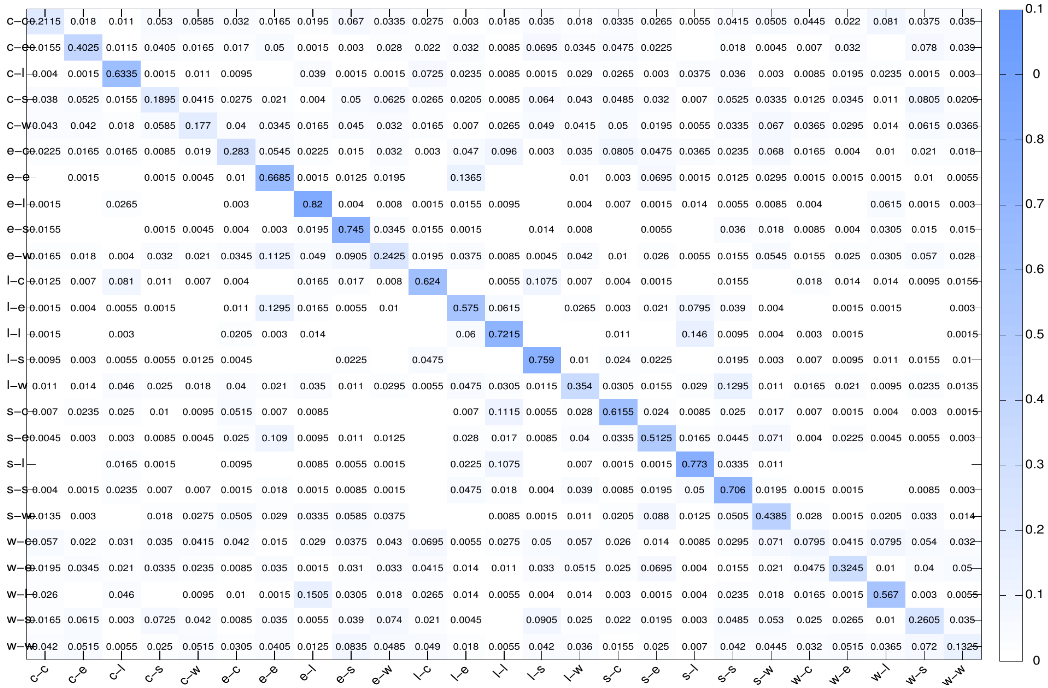

Figure 7: Confusion matrix when three receive nodes are utilised

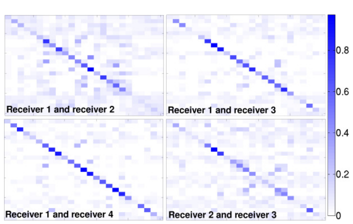

Figure 8: Confusion matrix with two receive nodes

In contrast, the accuracy drops with receiver 2 and receiver 3 or receiver 1 and receiver 2. This property can also be observed from table 6.

When only one receive node is utilised, however, the activities of the two individuals are hardly distinguished (cf. figure 10). In this case, the impact on the signal strength fluctuation by both individuals is merged in the signal observed at a single receiver.

Conclusion
We have considered the use of environmental RF-sensors to distinguish five basic classes in an indoor environment conducted simultaneously by two subjects not equipped with an antenna. For the classification with a k-NN classifier, we analysed the impact of the neighbourhood size k. Not surprisingly, the recognition accuracy increases when more sensors are utilised. We achieved good results with three or more receive nodes. Then, the 25 distinct classes could be well distinguished. For the distinction of activities conducted by a single individual, we considered the addition of receive nodes and unfavourable conditions in which the receiver is up to 5 meters separated from the location where activities are conducted. In the latter case, the dynamic activities crawling and walking have been harder to distinguish. In summary, we conclude that the distinction of simultaneously conducted activities from multiple subjects is feasible with sufficient count of receive devices. However, in order to arrive at a scalable approach in future studies, characteristic patterns for each single activity should be identified.

The present study has presented results from a case study in which the activities conducted simultaneously by two individuals can be distinguished. The study demonstrates the general feasibility to track multiple activities simultaneously from single-antenna receive devices. However, further studies have to show that these results can be generalised to diverse environmental settings and constellations of receive devices.

	c–c	c–e	c–l	c–s	c–w	e–c	e–e	e–l	e–s	e–w	l–c	l–e	l–l	l–s	l–w	s–c	s–e	s–l	s–s	s–w	w–c	w–e	w–l	w–s	w–w
c–c	0.105	0.033	0.024	0.046	0.056	0.039	0.029	0.013	0.066	0.040	0.031	0.009	0.023	0.027	0.020	0.053	0.029	0.015	0.037	0.067	0.037	0.043	0.075	0.045	0.038
c–e	0.028	0.338	0.018	0.034	0.037	0.018	0.066	0.002	0.008	0.026	0.021	0.015	0.014	0.058	0.018	0.065	0.027	0.006	0.013	0.009	0.018	0.040	0.017	0.068	0.035
c–l	0.014	0.009	0.396	0.014	0.015	0.011	0.003	0.034	0.011	0.007	0.083	0.046	0.040	0.020	0.047	0.045	0.014	0.048	0.045	0.010	0.018	0.021	0.035	0.008	0.006
c–s	0.030	0.056	0.022	0.119	0.043	0.026	0.024	0.011	0.062	0.047	0.033	0.011	0.019	0.064	0.034	0.058	0.042	0.024	0.045	0.027	0.026	0.046	0.019	0.081	0.032
c–w	0.054	0.066	0.022	0.048	0.113	0.031	0.027	0.018	0.044	0.038	0.028	0.013	0.027	0.046	0.031	0.067	0.022	0.014	0.023	0.060	0.036	0.035	0.031	0.062	0.042
e–c	0.027	0.029	0.022	0.022	0.015	0.186	0.047	0.018	0.021	0.034	0.007	0.034	0.085	0.010	0.047	0.066	0.069	0.042	0.029	0.085	0.021	0.017	0.023	0.027	0.018
e–e	0.008	0.024	0.000	0.004	0.005	0.022	0.553	0.015	0.013	0.025	0.010	0.121	0.003	0.013	0.011	0.010	0.060	0.011	0.015	0.045	0.004	0.007	0.005	0.009	0.008
e–l	0.002	0.002	0.022	0.002	0.004	0.008	0.037	0.694	0.003	0.015	0.002	0.020	0.005	0.001	0.025	0.015	0.005	0.010	0.030	0.024	0.011	0.002	0.054	0.004	0.004
e–s	0.022	0.003	0.005	0.015	0.011	0.005	0.008	0.013	0.691	0.037	0.007	0.005	0.003	0.008	0.021	0.002	0.002	0.011	0.030	0.019	0.013	0.010	0.027	0.016	0.017
e–w	0.020	0.031	0.009	0.027	0.024	0.032	0.095	0.057	0.082	0.189	0.024	0.033	0.008	0.018	0.056	0.010	0.029	0.007	0.013	0.057	0.023	0.029	0.029	0.066	0.032
l–c	0.010	0.014	0.065	0.012	0.009	0.007	0.013	0.028	0.014	0.013	0.438	0.044	0.019	0.155	0.021	0.005	0.007	0.003	0.013	0.000	0.021	0.031	0.032	0.013	0.017
l–e	0.003	0.004	0.030	0.001	0.002	0.019	0.132	0.017	0.006	0.010	0.025	0.444	0.072	0.001	0.017	0.004	0.028	0.103	0.061	0.012	0.003	0.004	0.001	0.001	0.001
l–l	0.005	0.002	0.013	0.005	0.003	0.026	0.002	0.005	0.003	0.001	0.012	0.072	0.584	0.000	0.009	0.019	0.019	0.173	0.033	0.009	0.006	0.001	0.001	0.000	0.001
l–s	0.010	0.006	0.009	0.013	0.013	0.005	0.008	0.004	0.018	0.003	0.063	0.001	0.001	0.649	0.011	0.014	0.058	0.003	0.014	0.026	0.007	0.019	0.007	0.027	0.012
l–w	0.010	0.013	0.051	0.015	0.019	0.040	0.033	0.068	0.030	0.034	0.018	0.039	0.034	0.014	0.235	0.039	0.028	0.037	0.092	0.028	0.031	0.030	0.018	0.025	0.017
s–c	0.022	0.025	0.032	0.020	0.027	0.051	0.009	0.027	0.000	0.006	0.002	0.010	0.089	0.027	0.029	0.456	0.040	0.017	0.019	0.026	0.015	0.016	0.014	0.009	0.012
s–e	0.013	0.008	0.011	0.012	0.006	0.037	0.088	0.008	0.012	0.014	0.004	0.038	0.022	0.064	0.021	0.033	0.412	0.044	0.040	0.055	0.006	0.027	0.004	0.020	0.004
s–l	0.003	0.002	0.019	0.004	0.002	0.020	0.007	0.007	0.013	0.004	0.002	0.060	0.149	0.002	0.004	0.006	0.026	0.551	0.085	0.021	0.003	0.002	0.005	0.003	0.002
s–s	0.007	0.003	0.031	0.007	0.007	0.004	0.020	0.024	0.037	0.002	0.006	0.048	0.030	0.003	0.043	0.009	0.019	0.098	0.560	0.027	0.003	0.003	0.002	0.006	0.003
s–w	0.027	0.003	0.006	0.013	0.020	0.054	0.053	0.036	0.041	0.039	0.000	0.022	0.014	0.021	0.023	0.031	0.079	0.039	0.054	0.304	0.023	0.014	0.028	0.026	0.029
w–c	0.041	0.039	0.030	0.031	0.044	0.040	0.021	0.036	0.039	0.042	0.068	0.012	0.027	0.034	0.072	0.053	0.018	0.008	0.032	0.051	0.068	0.051	0.061	0.043	0.038
w–e	0.038	0.044	0.034	0.035	0.029	0.015	0.026	0.007	0.034	0.039	0.045	0.013	0.014	0.054	0.054	0.040	0.072	0.005	0.018	0.019	0.034	0.232	0.016	0.043	0.038
w–l	0.019	0.018	0.043	0.011	0.011	0.019	0.005	0.124	0.041	0.027	0.052	0.017	0.007	0.013	0.019	0.010	0.007	0.013	0.023	0.018	0.024	0.012	0.427	0.018	0.022
w–s	0.026	0.068	0.009	0.058	0.039	0.024	0.036	0.012	0.051	0.058	0.027	0.005	0.003	0.079	0.034	0.028	0.037	0.007	0.042	0.048	0.030	0.037	0.017	0.181	0.043
w–w	0.049	0.046	0.020	0.036	0.047	0.032	0.034	0.025	0.061	0.059	0.040	0.014	0.009	0.054	0.043	0.028	0.033	0.012	0.024	0.046	0.042	0.056	0.052	0.063	0.074

Figure 9: Confusion matrix when two receive devices are utilised

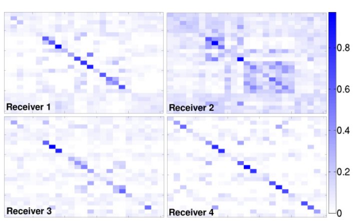

Figure 10: Confusion matrix with one receive node

In particular, we have considered feature samples from two individuals only and the study was conducted only on a single day. It is to expect that the accuracy deteriorates when the classification and training are further separated in time [5]. Furthermore, the placement of nodes will impact the accuracy of the recognition system. In particular, the floor is not the best location to recognise human activities [1].

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