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# 5G Ubiquitous Sensing: Passive Environmental Perception in Cellular Systems

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**Abstract**—While most RF-sensing approaches proposed in the literature rely on short-distance indoor point-to-point instrumentations, actual large-scale installation of RF sensing suggests the use of ubiquitously available cellular systems. In particular, the 5th generation of the wireless communication standard (5G) is envisioned as a universal communication means also for Internet of Things devices. In this paper, we investigate environmental perception capabilities in cellular systems, with special focus on the upcoming 5G communications standard. In particular, we analyze the perception capabilities of existing cellular installations in the GSM band, which is expected to be used for 5G IoT. Our instrumentation exploits a passive system capitalizing on environmental RF-noise. In addition, utilizing a prototypical 5G system with 52 OFDM carriers over 12.48 MHz bandwidth at 3.45 GHz, we consider the impact of the number and choice of channels and compare the recognition performance with acceleration-based sensing. Our results in realistic settings with five subjects suggest that accurate recognition of activities and environmental situations can be a reliable implicit service of future 5G installations.

## I. INTRODUCTION

The upcoming 5G cellular communication standard is expected to become the backbone of the IoT [1]. 5G capable devices will then be ubiquitously present. Apart from communication, their shared access to the wireless channel enables environmental perception [2], [3], [4]. However, unlike classical RF-sensing approaches that exploit WiFi, the distance between transmit and receive components is magnitudes larger in cellular systems, where the base station is likely located outside and on top of buildings. the larger distance and necessary penetration of building walls and other obstacles results in reduced signal strength at a receiver, and consequently lower recognition accuracy [?].

We study environmental perception in cellular systems, and especially focus on 5G. Our contributions are :

- 1) evaluation of device-free activity recognition accuracy in existing cellular systems exploiting OsmocomBB firmware [5]. We exploit GSM-band lower frequency range that is expected to be utilized for communication among 5G IoT devices. In particular, we investigate the detection of crowd size.
- 2) investigation of presence detection from a 5G prototype system featuring 52 OFDM carriers over 12.48 MHz

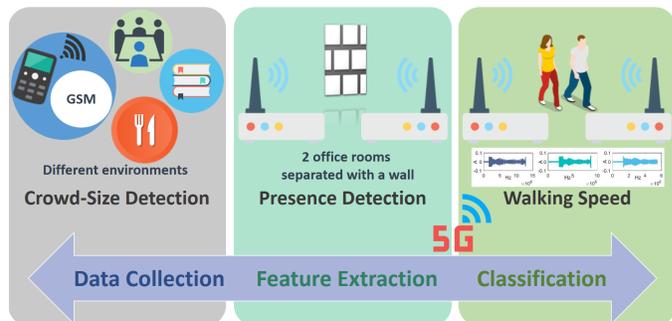


Fig. 1. Overview of our recognition approaches. Crowd-size detection is employed in the GSM-band, while for the presence and walking speed detection, data packets are transmitted via 52 OFDM carriers via a prototypical 5G system.

bandwidth at 3.4 5GHz in realistic noisy and crowded indoor spaces.

- 3) walking speed detection from the same 5G prototype system in indoor spaces and comparison to acceleration-based inertial measurement regimes.

For recognition, we investigate the use of multiple OFDM channels and derive an optimal choice of OFDM carriers for activity recognition. Since our investigation is tailored for IoT and other resource-limited mobile devices, we refrain from using phase-information but instead exploit information that can be readily extracted from signal-strength time series at resource limited devices.

Figure 1 gives an overview of the three different settings considered. The data traffic for recognition is generated by standard packet data transmission. This ambient traffic is not under the control of the system and not modified by us.

The rest of this paper is structured as follows. Section II introduces related prior work, section III describes the systems exploited in our studies, section IV details the perception and classification tool-chains and features for presence and walking speed recognition. Section VI discusses our results and section VII concludes our discussion. Part of this work, especially the considerations on walking-speed recognition, has been presented as a poster in [6].

TABLE I  
ACCURACY ACHIEVED FOR WALKING-SPEED RECOGNITION IN THE  
LITERATURE

Approach	Accuracy
FM-radio [14]	0.64
RSSI (Active) [18]	0.72
RSSI (Passive) [17]	0.78
Acceleration [19]	0.85
This work (cellular 5G)	0.95

## II. RELATED WORK

### A. Radio-vision

RF-based sensing of activities and gestures has been prominently studied in recent years, ranging from the recognition of gestures via Doppler fluctuation [3], [4] or CSI signal envelope [7], respiration rate exploiting Fresnel zones [8] as well as emotion recognition from phase and time-domain signal strength fluctuation [9], [10], [11]. Recognition of environmental stimuli via radio frequency fluctuation has become undemanding, as pre-installed infrastructure can be exploited [3]. This situation will further improve with upcoming 5G communication standards as it is expected that this technology will support a significantly larger number of devices to generate RF-traffic and will partly operate at higher frequency and larger bandwidth [12]. It will add continuous activity recognition capabilities to virtually all environments.

The above mentioned systems consider point-to-point indoor installations while our work in contrast focuses on cellular systems, specifically featuring 5G communication.

### B. Sensing of walking-speed

Walking-state and walking speed recognition has been exploited by various modalities, including RF-fluctuation, such as WiFi, FM-radio or software radios [2], [4], [7]. Walking speed is also used in a number of relevant applications for the IoT, such as fitness tracking, attention monitoring, and health [13], [14]. For instance, walking speed has been proposed as a reliable modality to detect movement disorders such as in Multiple sclerosis and elderly care [15]. Environmental sensing (e.g. RF-based) of walking speed and other activities, promises seamless, ubiquitous integration into environments and convenience for subjects as the sensing equipment need not be worn on the body [4].

The recognition of walking speed from RF-fluctuation has been considered from variance in FM radio signal strength [14], custom SDR [16] or RSSI [17].

Exploiting a prototype 5G OFDM system, developed at our department, we describe detection and classification of walking behaviors. We investigate the impact of sub-channel count and compare our results to accelerometer-based recognition.

To compare the results achieved in this work to the state-of-the-art, we summarize the accuracy achieved in previous work to the results presented in this paper in table I. While accuracy in radio-based walking speed recognition has already been nearly at level with inertial sensing approaches, exploiting further carriers over a larger bandwidth combined with low noise



Fig. 2. The canteen environment at different days and time of day

in the signal reception has the potential to achieve comparable or even better recognition accuracy (cf. section V-C).

## III. SYSTEM DESCRIPTION

This section describes our measurement systems for crowd size, presence and walking speed (cf. figure 1).

### A. Cellular system exploiting osmocombb

The current GSM-band is expected to be occupied as part of the 5G frequency bands. Especially, the lower frequency bands are reserved for resource-restricted devices and will establish the backbone of the IoT. To investigate environmental perception in these frequency bands, we use the OsmocomBB open source GSM baseband implementation. The firmware realizes the GSM protocol stack together with device drivers for the baseband chipsets. It runs on the host machine and the connected mobile device to access the wireless interface. We used Motorola C123 mobile devices as phone hardware. In particular, the OsmocomBB network monitor is capable to capture the RSSI of overheard packages. We use this information for the environmental perception.

1) *Crowd-size detection*: We investigate the recognition of crowd-size in a canteen environment at Aalto University. In particular, the phone was placed on a table in the entrance area of a canteen. The phone records RSSI information and from this establishes information about the crowdedness of the restaurant. In particular, we distinguish between rush-hour times and off-peak times. Recordings have been taken at different time of day and over several days (see Figure 2). Data used for training and testing the model have been chosen from different days. For classification, a support-vector machine (SVM) has been trained from mean, variance and entropy features. Features are generated from non-overlapping windows.

### B. Prototype 5G OFDM system

We utilize a prototype 5th generation communication system developed at our department. The system suggested by recent studies, uses sub-frames with separated control and data parts (see Figure 3) [12]. The system characteristics are depicted in table II. In contrast to other radio-based systems exploited for human activity recognition, it features a large sub-carrier spacing (240 KHz) to enable shorter symbol length. Consequently, this large sub-carrier spacing enables the system to operate at higher carrier frequencies and with improved robustness to phase noise compared to LTE systems [12]. The received data is a sequence of OFDM symbols with a gap of 200  $\mu$ s between

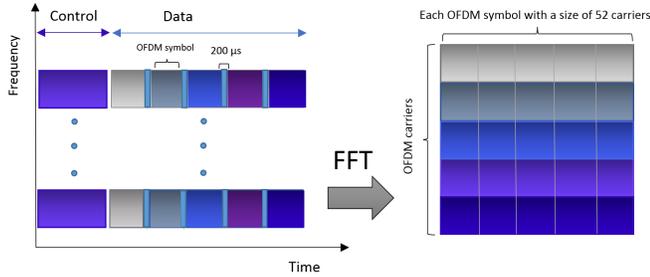


Fig. 3. OFDM carriers and symbols of our prototype 5G system

TABLE II  
5G PROTOTYPE SYSTEM CHARACTERISTICS

Characteristics	Value
Center Frequency	3.45 GHz
OFDM carriers	73 (52 for data)
One OFDM symbol length	4.16 $\mu$ s
Sub-carrier spacing	240kHz
Carrier Bandwidth	12.48MHz

each in time domain (see Figure 3). Data is sampled at 12.5 M samples per second. Figure 4 shows data streams received for various walking speed cases. The y-axis in the figure depicts the 52 data carriers, the x-axis shows the OFDM symbols received over time while their signal magnitude is color-coded.

1) *Presence detection*: For this experiment, we used universal software radio peripherals (USRP) devices for the instrumentations (USRP X310, covering center frequency up to 6GHz) as transmitter (Tx) and receiver (Rx). We utilized TPLINK omni-directional antennas with a gain of 18 dBi in both Tx and Rx sides. Tx and Rx are positioned in two distinct office rooms, separated by a concrete wall (see Figure 5).

2) *Walking speed detection*: Two USRP NI 2932 devices (covering center frequencies from 400 MHz to 4.4 GHz) were used as Tx and Rx devices with a maximum RF-bandwidth of 40 MHz. The TPLINK omni-directional transmitter antenna features a gain of 18 dBi and in receiver side a planar antenna with a gain of 5 dBi was employed (Figure 6 (a) and (b)). We

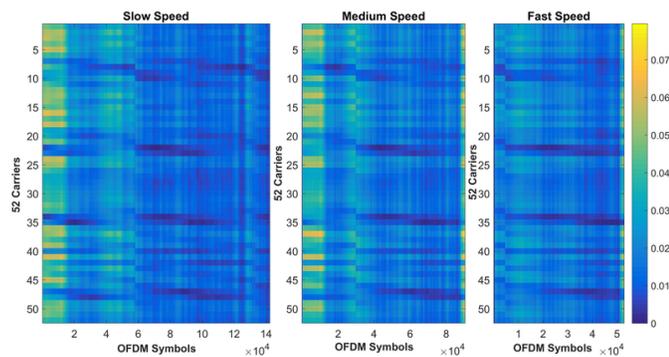


Fig. 4. Data transmitted over 52 data channels for the three walking speeds considered.



Fig. 5. The figure shows Rx and Tx side (respectively) which are separated with a wall in middle.



(a) Transmitter (b) Receiver (c) Set-up

Fig. 6. (a) Shows the employed transmitter with a laptop in order to control data transmission. (b) Illustrates receiver side with an employed monitor to control data transmission and (c) shows the corridor which experiments were executed and the arrow indicates the distance between Tx and Rx

executed measurements in an indoor corridor (Figure 6 (c)). The height, width and length of the corridor are 2.5 m, 2.2 m and 27 m respectively and the material of walls is bricks. Tx and Rx devices have been positioned over the floor at a height of 0.9 m and 1.5 m respectively and facing each other at a distance of 20 m.

### C. Acceleration sensing

For acceleration sensing we utilize a Samsung Galaxy S5 mobile phone equipped with a triaxial accelerometer at 50 Hz. We examine acceleration data using only y and z axis since our data featured low variance in the direction of the x axis (due to the straight walking movement conducted). Features in time domain are extracted from the magnitude data which consists of y and z-axis components and frequency domain feature is extracted from the z-axis (up and down) data only.

## IV. CLASSIFICATION TOOL CHAIN

### A. Feature extraction

We apply similar features in all cases considered, but adapted to the respective recognition systems. In particular, we exploit both time and frequency domain features and investigated mean, standard deviation, variance, root of the mean squared (rms), frequency spectral entropy, kurtosis and skewness. From these, we manually exploited various combinations in order to identify those which are most characteristic to describe the respective recognition cases. Best results have been achieved with mean, variance and entropy features. Also, several window sizes have been investigated.

For the crowd-size detection from GSM-band system, a support-vector machine (SVM) has been trained from mean, variance and entropy features which are generated from non-overlapping windows.

In the presence detection scenario, we applied the above features over a window of 60 milliseconds length. In the OFDM system, this window length translates to 300 OFDM symbols and  $60814\mu\text{s}$ , due to the gaps in the recording added to data length.

For the walking-speed detection case from the same prototype OFDM system, we again applied the same feature sets. Empirically we achieved the best result from non-overlapping windows of 20 milliseconds length. Each window length includes 100 OFDM symbols, which corresponds to  $203.38\mu\text{s}$  over time. For the acceleration-based consideration, we again utilize the same set of features as for the OFDM-based walking speed detection.

### B. Classification

Classification was conducted exploiting both the Matlab Classification Learner toolbox and python scikit-learn. For the crowd-size detection, we achieved best results with a SVN classifier while results for the other cases have been achieved with a KNN classifier. The choice of different classifiers has historical reasons as investigations have been started in different projects. In any case, since optimized toolboxes have been utilized in both cases, we do not expect significant impact on the classification results if methods were changed.

Training and testing was conducted in the crowd-size detection case exploiting data from different days for the respective training and testing sets. For the presence-detection case, we exploited five samples for each case (four cases) which we took one testing set (including 1 sample from each case) in a different day from training subsets. Consequently, we applied leave-one-subject-out cross validation. Finally, for the recognition of walking speed with acceleration and RF-data, we divided the data into 5 subsets, one for each subject, and again we employed leave-one-subject-out cross validation.

## V. EXPERIMENTAL SETTINGS

### A. Crowd-size detection

We chose a restaurant for crowd detection at our campus. The receiver (Motorola C123 mobile phone) was placed on the center table near the entrance of the restaurant. The RSSI were observed and recorded at different days and times of day. The three cases when the restaurant was empty, moderate rush and the peak hours were considered. At peak hours the queue of persons were moving close to the receiver during the whole observation period. In moderate hours there were persons moving randomly near the receiver and others farther away at the sitting area was also not as fully occupied as in peak hours. The peak time at the restaurant is 12.00 noon when it is almost overcrowded, while at 03.30 pm the restaurant was moderately filled. For empty tests we choose 06.00pm in the evening when the restaurant is totally empty.

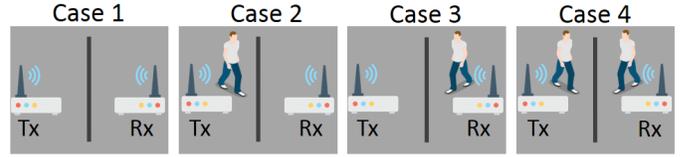


Fig. 7. The four cases considered for presence detection covering two neighboring office rooms.

### B. Presence detection

We investigated the detection of presence in indoor environments in which the transmit and receive devices are separated by furniture and a wall. In addition, we were careful to conduct the experiment on days where the offices have been partly occupied by other subjects to cover natural environmental noise. In the experiment we distinguish between an office in occupied or non-occupied state. In the occupied state, a person was moving freely in the office while in the non-occupied state, the office was only occupied by occasional other workers sitting and working in front of their computers. In addition, we generated special cases in which another subject is walking in proximity of the transmitter in order to investigate whether movement farther away from the receive device would impair the recognition performance. Measurements have been taken over a number of days and on several times of day. The four different cases considered are depicted in Figure 7.

- 1) Office with Rx device is occupied by office workers but no subject walks or moves in the proximity of Tx and Rx.
- 2) A single subject moves freely in the proximity of Tx (noisy case).
- 3) A single subject moves freely in the proximity of Rx while no subject moves near Tx.
- 4) A single subject moves freely in the proximity of Rx and another subject moves freely in the proximity of Tx (noisy case).

We repeated each of the four cases five times over the course of several days where each recording lasted for at least five minutes. Both environments are natural office environments and differed from each other in the furniture installed (cf. figure 5).

### C. Walking speed recognition

In order to detect walking speed, we measured features from five young healthy persons including three males and two females aged 23-30. Each person walked the same distance at three speeds: slow (0.7 meters per seconds (m/s), medium (1.3 m/s) and fast (2.2 m/s)) [20]. The idea behind choosing these speeds is gait transition from human walking and running. Individuals have two distinct gaits (walking and running) and the natural transition point from walking to running is 2.2m/s [18].

We used a Metronome to help participants maintaining walking speed during experiments. Participants practiced using metronome before the experiments [21], [22]. As further

TABLE III  
ACCURACY ACHIEVED FOR DIFFERENT SET OF CLASSES OF PRESENCE DETECTION

Set of classes	Accuracy
(A) case 1 and 3	0.928
(B) case 1+2 and 3+4	0.798

orientation, the ground was marked with a tape in distances of 1 meter and 50cm between transmitter and receiver. We exploited accelerometer data in order to compare with RF results. During the experiment, subjects put a mobile phone into the front pocket of their trousers while walking between transmitter and receiver.

For acceleration sensing, the phone recorded only acceleration sequences and it was not utilizing the RF interfaces. The subjects wore the phone in the front pocket of their trouser, which is a reasonable location for walking speed estimation, since sensing at the lower spine of the body has been shown to achieve higher accuracy for walking speed estimation [23]. Since we aimed to achieve realistic accuracy, we accepted possible sensor displacement or rotation as natural measurement noise.

## VI. RESULTS

### A. Crowd-size detection

For SVM classifier with mean, variance and entropy features, we achieved an overall accuracy of 0.809.

### B. Presence detection results

For presence detection, we utilized 26 equally distributed carriers from all 52 carriers<sup>1</sup>. Table III shows the overall accuracy achieved for all cases.

Naturally, the best result has been achieved for the non-noisy recognition cases (A) where no subject caused noise close to the transmitter. However, movement farther away from the receiver has only small impact on the recognition accuracy. We can see this by including the cases where a person has been moving close to the Tx side. In particular, we combined cases 1 and 2 as well as cases 3 and 4 (cf. figure 7). We observe that, despite the noise generated by the person in proximity to the transmitter, the recognition performance is degraded only gently. The system is robust to such environmental noise and can still detect the overall situation correctly with an accuracy of 0.798.

1) *Walking speed results*: In this case, we investigate the accuracy for walking-speed recognition from our 5G prototype system and compare the achieved accuracy with inertial-measurement-based acceleration sensing and recognition of walking speed. In addition, we investigated the impact of the number of carriers considered on the recognition performance.

We exploited various combinations of carriers and carrier count selected and compared the results achieved to the accuracy reached for acceleration sensing. For this purpose, we

<sup>1</sup>see section VI-B1 for a discussion of the impact of the choice of OFDM carriers



Fig. 8. Confusion matrices and average accuracy for the recognition of three walking speeds from OFDM and acceleration data, recognized by a K-NN classifier for six distinct carrier selections.

constructed six cases in which selected carriers were equally distributed between all carriers. Case (a) features only a single carrier (26th, center carrier). Case (b), case (c), case (d) and case (e) represent thirteen, twenty-six, thirty-nine and 52 carriers, respectively. Case (f), finally, represents acceleration data. Results are summarized in Figure 8.

The confusion matrix for case (a) (Figure 8 (a)) reveals that slow speed is well distinguished from fast speed but medium speed is partly confused with fast speed. The overall accuracy achieved in this case is 0.662. This single-carrier case is most similar to traditional RSSI-based recognition but with higher sampling frequency and sampling accuracy. We gradually increase the number of OFDM carriers considered from case (b) to (e) which, in turn is rewarded by an increase in the recognition accuracy up to 0.946 in the 26-carrier case. With thirteen carriers (case (b)), already the confusion between medium and fast speed can be reduced, resulting in a higher average accuracy of 0.68. However, medium speed still possesses low accuracy of 75%. This trend continues with the consideration of further carriers and results in a rise in accuracy with each additional 13 carriers considered. Figure 8 (c) displays the third case in which we can observe the

highest accuracies for slow, intermediate and fast speed (94% and 95% respectively). For the fourth scenario, we considered thirty-nine carriers and we achieved an average accuracy of 92.66% (Figure 8 (d)). We examine the fifth case by exploiting all fifty-two carriers over OFDM symbols, which results in a drop of 0.06 in accuracy (see Figure 8 (e)). We account this to the overlapping and, due to noise, partly contradictory information obtained from the neighboring carriers. According to figure 8 (c), the best result is achieved when we applied only half of the available carriers (26), leaving a spacing of one carrier between each considered OFDM carrier.

We also plot the confusion matrix for the acceleration case (case (f) in figure 8 (f)) for comparison. The overall accuracy achieved is 0.7033, which demonstrates that we are able to reach comparable, or potentially better accuracy from RF-sensing than what is possible from classic acceleration sensing. As can be seen from figure 8 (e), accuracies of 67% and 72% are observable from slow and medium speed due to their interference. However, acceleration-based process was able to infer the speeds with an average accuracy of 70% only.

## VII. CONCLUSION

We have investigated environmental perception in RF-based cellular systems. In particular, we have considered the detection of presence and person count in existing GSM instrumentation, as well as the detection of presence and walking speed from a prototypical 5G communication system. We evaluated the results in real environments achieving accurate detection capability reaching 80.9%, 92.8% and 95% in three study cases respectively. The results showed promising performance in terms of accuracy for ubiquitous motion detection in cellular systems and from IoT-class devices.

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