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Towards battery-less RF sensing

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Abstract—Recent work has demonstrated the use of the radio interface as a sensing modality for gestures, activities and situational perception. The field generally moves towards larger bandwidths, multiple antennas, and higher, mmWave frequency domains, which allow for the recognition of minute movements. We envision another set of applications for RF sensing: battery-less autonomous sensing devices. In this work, we investigate transceiver-less passive RF-sensors which are excited by the fluctuation of the received power over the wireless channel. In particular, we demonstrate the use of battery-less RF-sensing for applications of on-body gesture recognition integrated into smart garment, as well as the integration of such sensing capabilities into smart surfaces.

1. Introduction

Gesture and activity recognition from electromagnetic signal reflections off passive objects or subjects has drawn significant interest. Started by initial studies utilizing software radio devices, that had become affordable around that time, researchers have further focused on WiFi based sensing. Recently, and spurred by the technological advance towards millimeter Wave RF equipment with multiple antennas, as well as mmWave radar hardware, impressive sensing performance of minute gestures has been demonstrated.

While the development was first driven by algorithmic advances, the extraction and processing of features in time, frequency and phase domain, recognition concepts such as fingerprinting, radio tomography, FMCW radars, or the utilization of fresnel effects, recent advances are driven by technological advance in the sensing hardware, such as higher frequencies, more antennas, or alternative technologies (e.g. LoRa). The field moves away from exploiting existing infrastructure for a cheap and implicit sensing modality, to increasingly specialized expensive hardware.

We believe that there is another direction for RF-sensing which is currently unexplored: Low-power environment integrated passive sensing for truly ubiquitous environmental perception. In particular, we exploit a set of commercial RFID-based RF-power sensors for environmental perception. The hardware has been modified to exploit the voltage changes observed due to changing harvested electromagnetic power for environmental perception. In particular, we envision applications where a grid of sensors is integrated into wallpapers or tables, or also, using conductive garment, into smart textile for gesture sensing (cf. figure 1).

Figure 1. Perception through battery-less sensors integrated into objects

2. Related Work

Radio-sensing, the interpretation of time, frequency or phase related features observed at a wireless receiver, for environmental perception has been an active field of research throughout the past decade [1]. In particular, recognition approaches range from interpreting narrow-band time-domain features for simple presence and movement-based predictors [2] to frequency-based approaches exploiting high frequency and wide bandwidth for the recognition of minute movement [3]. In recent years, radar-based mechanisms have become popular [4] and we are witnessing the integration of radar-based sensing technology into off-the-shelf commercial devices [5].

Summarizing, the field is moving collectively towards ever wider bandwidth, higher frequencies, and multi-antenna sensing hardware [6]. On the other hand, due to its ubiquitous availability, the radio channel is an excellent candidate for a ubiquitous common sensing modality. It might be an enabler for the visions of smart dust [7] and even for the broad notion of Ubiquitous computing if the sensing can be conducted efficiently. Essentially, an energy-neutral sensing mechanism is required in order to integrate RF-sensing into everyday objects, smart environments, and intelligent textile [8]. The recent advances in RFID, backscattering as well as energy harvesting are overlapping with the notion of RF-sensing: All parasitically exploit energy from ambient RF-signals to achieve their operational principle. In particular, for simple narrow-band time-domain based environmental perception, a complex receiver with multiple antennas, signal oscillators, and expensive feature extraction and processing is not needed. We exploit changes in the voltage level of a battery-free RF-energy meter (the farsens EVAL01-Photon-R) for environmental perception.

This work is related, for instance, to [9], who recognize

Figure 2. The RF-field detector utilized in our studies (left) and the arrangement of sensors for the environment-integrated experimental setting.

a gesture pattern drawn with an RFID tag on a surface surrounded by three 10x10cm rfid reader antennas. The system exploits passive sensing with multiple hypothesis tracking to recognize motion patterns with an accuracy of 93%. This is similar to the concept of the wireless identification sensing platform project [10] which allows monitoring of the movement of a tagged object. Recognition of tag-free objects through RFID has been discussed in [11], however, assuming signals reflected from the tags and a recognition of the signal at a remote reader device. Gesture recognition utilizing passive RFID devices has been demonstrated in [12], [13]. Their system exploits a tag-reader based approach where the gestures are recognized from motion patterns observed at the reader device. In addition, various authors have recently suggested the use of backscatter devices for the use in RF-sensing, such as [14]. The authors of [15] propose an activity recognition system exploiting backscatter tag-to-tag transmissions which is measured via systematic multiphase probing. Both systems expect a reader device to read out the channel fluctuation.

In contrast to all prior work, we propose to conduct the gesture recognition locally on the battery-less antenna-device, hence don't backscattering the signal but to observe and interpret signal fluctuation locally. Paired with energy harvesting circuits, our scheme hence has the potential for maintenance-free battery-less continuous operation.

3. Methodology and Experiment

We utilize the farsens EVAL01-Photon-R Radio field sensor (cf. figure 2), to detect motion and gestures. In particular, we conduct two studies, investigating distinct realizations of the batter-less sensing concept: integration of the sensors with smart textile using conductive garment (on-body wearable sensor case), as well as integrating a matrix of sensors into furniture for gesture interaction (environment-integrated sensing).

Since the EVAL01-Photon-R sensor is not natively designed for RF-sensing from voltage fluctuation (it is manufactured to light an LED conditioned on the strength of

Figure 3. Environmental settings utilized in our experiments

the surrounding RF field), we attached a photo diode and a lead resistor on top of the LED of the sensor to capture the varying light intensity of the LED. In this prototype stage, we utilized an arduino device to read out the data from the photo diode.

To be able to generate and direct the electromagnetic signal to the radio sensors, we used an NI USRP-29312 at 868MHz and 200 MHz bandwidth, amplified (P1dB 21 dBm). The antenna utilized has a 8dBi gain. Note that a typical EIRP for RFID reader systems is in the order of 36 dBm.

For the first study (on-body wearable sensors), we attached three sensors each arm of the person (wrist, elbow, shoulder) as displayed in figure 3a. The antenna was located in 0.5-1m distance from the subject, which conducted six different gestures: turn-left (turnleft), turn-right (turnright), raise left arm while turned right (rightblock), raise right arm while turned left (leftblock), raising the right arm (rightarm), raising the left arm (leftarm). Three subjects participated in the study and each gesture has been repeated 30 times, for a total of 540 gesture samples.

For the second study (environment-integrated sensors), we arranged nine sensors as a 3x3 grid (distance between sensors: $15\text{cm} \approx \frac{1}{2}\lambda$) underneath a table and in approximately 0.8m distance to the antenna on top of the table (through the wooden table surface). We were interested in the performance to recognize six gestures performed by a subject on top of the table. Again, three subjects participated and performed a total of 540 gestures (30 repetitions of each gesture): typing on a keyboard (typing), swipe from right to left over the table with the right arm (rightswipe), swipe from left to right with the left arm (leftswipe), writing on a piece of paper with the left hand (leftwriting), writing on a piece of paper with the right hand (rightwriting), and finally the empty table where the subject is absent and no gesture is performed (blank).

4. Evaluation and Results

We trained a k-nearest neighbour classifier in both studies, utilizing leave-one-person-out cross-validation. In particular, note that the signal strength was affected distinctly by different gestures (see Figure 4 of sensor data). Therefore, we used simple time-domain features: mean, variance,

Figure 4. Variation of signal strength caused by different gestures

slope and quadratic polynomial coefficient of the recognized gesture over time. These features have been calculated for each sensor separately. The slope value that describes a general trend of the sensor data is computed by averaging the difference between successive values in the sequence $a_{i \in \{1 \dots n\}}$:

$$\frac{1}{n} \sum_{i=1}^n |a_i - a_{i-1}| \quad (1)$$

Furthermore, the quadratic polynomial coefficient is generated from the coefficients of the quadratic polynomial approximating the sequence. The polynomial $f(x) = a + bx + cx^2$ is obtained by minimizing the squared error:

$$E(a, b, c)^2 = \sum_k (a_k - f(x_k))^2 \quad (2)$$

In the on-body sensing case, we aim to recognize gestures performed by the subject while wearing the sensors. The recognition performance for this study is depicted in the confusion matrix in figure 5a. We observe that the recognition accuracy is acceptable given the simple sensing platform, and achieving an overall recognition accuracy of 85.33%. Most notable confusion is observed between the activities when the subject is turned to the left (right) and raising the right (left) arm and the movement of the right (left) arm while facing the sensor. This is reasonable since the movement is identical in both cases, while the subject has turned to the side.

For the second study (environment integrated sensors), we aim to recognize the activities performed by the subjects when the sensor is integrated into the environment. In our case, the sensor plate has been mounted underneath the table so that gestures and activities which are conducted on top of the table by a person sitting and working on the table can be recognized. The person is not wearing any sensors in this case.

The results are summarized in the confusion matrix in figure 5b. Not surprisingly, the blank gesture (no subject

(a) On-body sensing case

(b) Environment-integrated sensing

Figure 5. Confusion matrices for both experimental settings (k-NN)

and no gesture) is clearly identified from all six gestures conducted. Overall the recognition accuracy is remarkable with an overall accuracy of 97.38% and the lowest accuracy (writing with the right hand) at 0.93%. The largest confusion is observed between the activities of writing with the left hand and writing with the right hand. Again, this result is reasonable, since the subjects have been leaning over the table for both activities and the position is naturally similar across subjects and for these two activities.

5. Limitations

In our preliminary investigation, hardware prototypes have been used to demonstrate the concept of battery-less sensing from body-worn or integrated passive RF power meters. Therefore, we were not able to investigate other relevant aspects of the technology, in particular, with respect to usability and energy efficiency.

For an actual instrumentation, we envision applications in which the sensor is integrated into smart textile, using conductive garment (on-body sensing), or integrated into furniture, such as a table or desk or also printed e.g. in wallpaper (environment-integrated). Woven into a textile, printed on a wallpaper, or integrated into furniture, the long antennas of the passive sensing devices can be hidden and do not further disturb or hinder usability during movement or interaction with the sensors.

In our prototype evaluation, we have used photodiodes, read out by arduino devices to generate proof of the general concept of the system. Because of this, the prototype instrumentation has not energy-sustainable. In an actual instrumentation, we envision energy harvesting circuits [16] that power an ultra-low microprocessor from the energy harvested through the long RF antennas [17], [18] for battery-less operation. The interested reader is referred to the good overviews available on the topic, for instance, [19]–[22]

We have investigated the system only with three subjects and only exploiting 2x6 gestures in both cases. Therefore, the reader is advised to cautiously draw general conclusions from the reported results.

6. Conclusion and Future Work

We have investigated passive Device-free activity recognition utilizing battery less RF signal strength detectors.

In our prototype setting, we have used photodiodes attached to arduino devices to be able to interpret the fluctuation in the strength of the RF field. We have been able to demonstrate that the system already with as few as six or nine sensors is capable of recognizing meaningful gestures and activities from a small set of simple, narrow-band, time-domain features. In particular, recognition accuracies of 85% and 97% have been reached. We have used a machine learning approach (k-nearest neighbours), which has a classification accuracy which is logarithmic in the number of training samples when using, for instance, kD-trees or ball-trees to store the samples. On the other hand, the storage requirements for this classifier are linear in the number of samples. Future implementations may decide to optimize accuracy, storage or computational load with respect to the application at hand. We remark that, in our case, to recognize six distinct activities or gestures, only 360 samples have been used for training (leave-one-subject-out crossvalidation), so that the computational and storage demands are negligible.

The two scenarios we considered comprise an on-body sensing scenario where the subject was equipped with three sensors on either arm and an environment-integrated scenario in which we deployed the sensors underneath a desk. The on-body sensing case refers to applications in which the sensor is integrated into smart textile, using conductive garment. For the environment-integrated scenario, we envision the sensors to be integrated into furniture, such as a table or desk or also printed e.g. in wallpaper to enable battery-less perceptive spaces.

In our prototype evaluation, we have collected labelled data samples in which the relevant gestures and activities have been manually segmented. Future work has to show that an automatic segmentation of the data is possible to isolate meaningful segments and to spot those sequences in the data stream that actually refer to activities.

Furthermore, the population of subjects employed in this preliminary study has been limited to only three subjects. Future work with larger populations of subjects has to show that the results can indeed be generalized for actual instrumentation and pervasive applications.

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