RF-BASED ANALYTICS GENERATED BY TAG-TO-TAG NETWORKS

M. Stanaćević, Y. Karimi, G. Feng, J. Ryoo, A. Athalye, S. Das,** and P. M. Djurić*

Department of Electrical and Computer Engineering, Stony Brook University
*Department of Computer Science, SUNY, Korea
**Department of Computer Science, Stony Brook University

ABSTRACT

We have developed a type of RFID tags that can communicate with each other directly if there is an RF signal in their environment to support backscattering. These tags are passive and they can form a tag-to-tag network. Our tags communicate by what we refer to as multiphase probing. With this technique, we basically explore the backscatter channel by reflecting the incident RF signal with different changes in the phase. We define a measure of the backscatter channel, which we call backscatter channel state information (BCSI). The BCSI is composed of backscatter channel phase, backscatter amplitude, and change in baseline excitation level. When acquired over time, this measure provides rich RF analytics that can be used to extract various types of information from the environment of the tags by signal processing/machine learning methods. We show in the paper that this analytics is invariant w.r.t. to some variables including the deployment environment. We provide results from experiments with our tags that demonstrate the invariance of the BCSI.

***Index Terms*—** RFID, Internet-of-Things, multiphase probing, BCSI estimation, tag-to-tag networks

1. INTRODUCTION

In this paper, we address a network of RFID tags that can communicate with each other directly in the presence of an independent RF signal, which can be generated by a local exciter or can simply be an ambient signal [1, 2, 3]. We refer to this type of network as a tag-to-tag network. The tags of the network are passive and inexpensive and yet have the ability and intelligence to communicate directly with tags that are in their proximity. It is not difficult to imagine how such networks can play a prominent role in the up-and-coming Internet-of-Things (IoT). These tags can readily be attached to objects, can easily be deployed in large scales and can sense activities and interactions around them, as illustrated in Figure 1.

Passive tag-to-tag communication is a relatively new technology [1, 4]. Electromagnetic models for such communication were addressed in [5], and there have been various efforts to advance this technology. One is presented in [1], where commercial TV signals were exploited for excitation, and where communication ranges of a fraction of a meter were reported. In an effort to extend the range of the tag-to-tag link, the authors of [3] implemented a CDMA encoding. Another approach to increase the communication range in tag-to-tag networks was to build customized multi-hop network architectures and routing protocols [6].

In the past few years, we have actively conducted research on tag-to-tag networks, and they range from efforts to design better hardware for the tags [7, 8], to tracking of events with these networks [9]. More recently, we have explored the possibility to use the network as a device-free activity recognition system [10]. This is possible because our tags for communication exploit multiphase probing, which amounts to reflecting the incident RF signal during backscattering with different phases of the reflected signal. This allows us to define backscatter channel state information (BCSI) and enables the system of tags to recognize activities. In this paper, we make a further claim that the BCSI is invariant w.r.t. changes in deployment environments, human subjects, location within deployment environment, and different deployment locations. This feature is of great practical value in the use of these tags. We demonstrate the invariance with experiments conducted with our tags. Finally, it goes without saying that the data acquired by our tag-to-tag network provide a number of challenging problems from the areas of signal processing and machine learning.

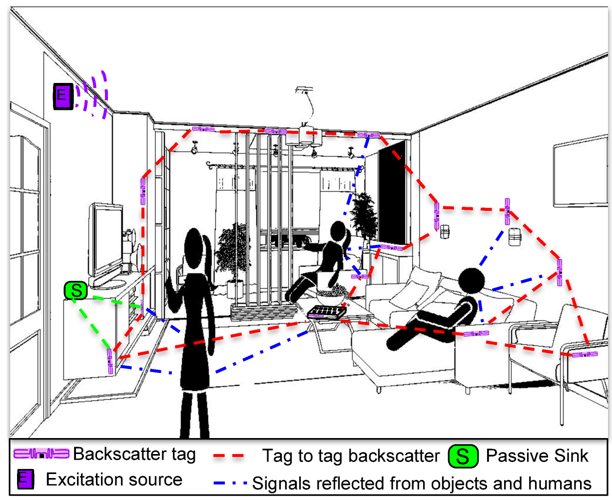

Fig. 1: A network of tags in a living space.

The paper is organized as follows. In the next section, we describe the tag-to-tag networks and the notion of channel estimation. In Section 3, we explain the RF analytics of our tag-to-tag network, and in particular the BCSI. In the following section, we address the invariance of the RF analytics. In Section 5, we provide experimental results with our tags. We conclude the paper with final remarks in Section 6.

2. TAG-TO-TAG NETWORKS

The backscattering communication principle until recently has been mostly limited to RFID systems [11, 12, 13, 14, 15]. A standard RFID system is comprised of an RFID reader, a computationally powerful device with active radio and ability to cancel the emitting

RF signal from the signal the reader is receiving. For tag-to-reader communication, the tag simply modulates its antenna reflection coefficient by switching between two impedances that terminate the tag antenna circuit [11], which effectively modulates the reflected signal back to the reader. The active reader demodulates this signal by employing IQ demodulation and active cancellation of the interfering carrier signal. However, the large scale applications of RFID systems have been mostly limited by the infrastructure cost of RFID reader deployment.

Enabling tag-to-tag communication based on the backscattering principle eliminates the need for RFID reader in the system. The added complexity in the RF tag capable of the tag-to-tag communication lies on the receiving side. The receiving (Rx) tag has to be able to resolve a low modulation index signal reflected by the transmitting (Tx) tag. A conventional RFID tag is able to resolve a signal from a transmitting RFID tag only on a distance that is a fraction of a meter [4, 5]. With integrated signal amplification after envelope detection on the RF tag, the range of tag-to-tag link is extended to a few meters [7, 3]. RF tags can then form a network transforming a conventional centralized system with an RFID reader to a distributed system. The tag-to-tag network only requires the presence of an RF signal in the environment. The RF signal can be either an ambient signal from WiFi APs or TV towers, or can originate from a dedicated exciter device that emits continuous wave (CW) signal with zero intelligence.

2.1. Tag-to-tag channel estimation

Techniques that are mostly used for activity recognition of a person that does not carry or wear any device (device-free) rely on analysis of wireless channels that ingrain information on reflections from a person and other living beings and objects in the environment [16, 17, 18]. Passive RF tags cannot perform IQ demodulation in order to estimate tag-to-tag channels due to their limited power budgets. Tags have to rely on passive envelope demodulation that only obtains the amplitude of the received signal.

To describe the proposed technique for estimation of tag-to-tag channel, let us observe the following scenario with a dedicated exciter and Tx and Rx tags, as shown in Fig. 2. For simplicity of the derivation, we assume that the Tx tag switches between two states, open circuit and reflection with phase ϕ. First, when the antenna circuit of the Tx tag is open, the Rx tag only receives the signal from the exciter, i.e.,

$$v_{R1}(t) = A_E(t)e^{j(\omega t+\theta_E(t))}, \tag{1}$$

where v_{R1} is the signal received at the Rx tag in state 1. The symbols A_E and θ_E are the amplitude and the phase of the *exciter-Rx* channel and are dependent on the reflections from the environment. The impedance of the antenna circuit is then changed, such that the Tx tag reflects the incident RF signal with a phase ϕ. The signal received at the Rx tag combines the reflected signal from the Tx tag and the direct path signal from exciter

$$v_{R2}(t) = A_E(t)e^{j(\omega t+\theta_E(t))} + A_B(t)e^{j(\omega t+\theta_B(t)+\phi)}, \tag{2}$$

where A_B is the amplitude of the backscatter and θ_B is the phase of the *exciter-Tx-Rx* channel. The baseband signal obtained at the Rx tag is the difference between the output of the envelope detector in the two states. When the amplitude of the backscatter signal A_B is much smaller than the amplitude of the excitation signal A_E, the difference between the two amplitudes simplifies to

$$\begin{aligned} \Delta v_R(t) &= v_{R2}^{amp}(t) - v_{R1}^{amp}(t) \\ &\approx A_B\cos(\phi + \theta_B(t) - \theta_E(t)). \end{aligned} \tag{3}$$

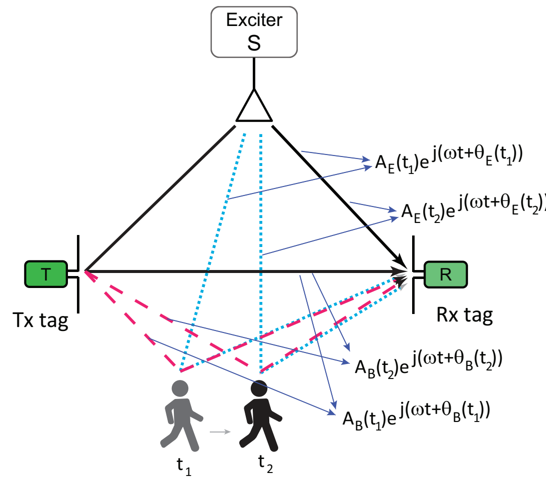

Fig. 2: The direct and reflected signals in backscattering tag-to-tag link scenario with a person present in the vicinity of the tags.

We define the backscatter channel phase as $\theta_{BC}(t) = \theta_B(t) - \theta_E(t)$.

To estimate the backscatter tag-to-tag channel, we have to estimate the amplitude and phase A_B and $\theta_{BC}(t)$. As the tags cannot directly measure these channel parameters, we exploit that in

$$\Delta v_R = A_B\cos(\phi + \theta_{BC}), \tag{4}$$

the phase ϕ is deterministic and set by the Tx tag. If the modulator of the Tx tag varies the phase ϕ, one can obtain the amplitude and phase of the backscatter signal according to

$$\begin{aligned} \theta_{BC} &= \frac{\pi}{2} - \phi\Big|_{\Delta v_R=0}, \\ A_B &= \Delta v_R\Big|_{\phi=-\theta_{BC}}. \end{aligned} \tag{5}$$

The modulator of the Tx tag can be designed to operate in a number of states, with a set of discrete phases $\phi_1, \phi_2, \ldots, \phi_N$, where N is the number of total states at which the modulator of the Tx tag backscatters. The discrete reflection phases ϕ_1 to ϕ_N are chosen to uniformly cover the range from 0 to π. The phase θ_{BC} is estimated based on the value of ϕ that results in Δv_R being equal 0. With discrete number of states, θ_{BC} is estimated from a weighted interpolation of two phases adjacent to zero-crossing of Δv_R. The amplitude A_B is obtained by weighted interpolation of $\Delta v_{R,k}$ between the same two phases, and the coefficients of this interpolation will be the same as those used in the estimation of θ_{BC}. The number of phases N depends on the required resolution of the estimation of A_B and θ_{BC}, the signal-to-noise ratio (SNR) of the received baseband signal and the data rate of the tag-to-tag link.

3. RF ANALYTICS

Since the human body reflects wireless signals, any activity in the vicinity of the tags alters the wireless channels around them in specific ways. Hence, by using the collated channel measurements from all over the tag network, the system can infer a wealth of analytic information about the environment and its occupying objects and humans.

We cannot measure the dynamics of the *exciter-Rx* channel using the presented technique since we cannot control the phase of the signal emmitted by the exciter. However, recording the changes in the excitation level A_E provides valuable supplementary information about this channel. Based on the described technique, we formulate a measure for the backscatter channel referred to as *backscatter channel state information (BCSI).* This consists of the following three quantities: *1) backscatter channel phase θ_{BC}, 2) backscatter amplitude A_B, and 3) change in excitation amplitude between two sampling intervals ΔA_E.* The BCSI vector recorded for a specific activity in an environment will have similar signature to the same activity performed in a different environment, as well as activity performed by a different person [10].

The BCSI vector serves as a feature vector which forms the basis of activity recognition. Once there is activity detected in the presence of two tags, the Tx tag enters a multi-phase probing (MPP) backscatter, in which, in a single MPP cycle, it backscatters with discrete reflection phase ϕ_1 to ϕ_N. For each probing cycle, the Rx tag computes the BCSI vector for that cycle, $\mathbf{h}(t)$. During the activity, the BCSI vector is sampled, where the sampling rate is sufficiently higher than the frequency/speed of the activities. The determination of the sampling rate is also driven by the energy budget of the Rx tag which limits the backscatter data rate and the number of discrete reflection phases. The sampled BCSI vector carries the distinctive signature of a specific event and is then used for classification.

4. THE INVARIANCE OF THE RF ANALYTICS

The use of the proposed BCSI measure for activity recognition with similar analytics is particularly attractive since the performance of such a system would be agnostic to the environment within which it is deployed. In the previous section, we have introduced the BCSI vector which contains the backscatter channel phase, backscatter channel amplitude, and the change in baseline excitation level. This vector is denoted as follows:

$$\mathbf{h}(t) = [\theta_{BC} \;\; A_B \;\; \Delta A_E] \,. \tag{6}$$

In order to perform activity recognition, the Tx tag sends out the MPP signal continuously for a few cycles. For each cycle t, the Rx tag computes the BCSI vector $\mathbf{h}(t)$. These continuous BCSI samples are then conveyed to an analytic center for processing. Here the individual components of the BCSI are parsed for certain dynamic variation patterns. Such patterns in each component jointly form an event signature which is used to classify the detected event. It is important to note here that *all analytics and event recognition is performed based on the dynamic variation patterns in the BCSI vector components and not their absolute value*. This results in the following vital invariance properties of the system which greatly enhance its robustness and use in practical situations:

1. Invariance w.r.t. changes in the deployment environment: Changes in the deployment environment such as static objects and clutter does not require retraining of the system.
2. Invariance w.r.t. to human subjects: Event recognition performance remains the same for different humans irrespective of the physical size and shape of the subject compared to the subject used for training the system.
3. Invariance w.r.t. to location within the deployment enviroment: Since the proposed system will inherently have a dense deployment of tags, and because tag-to-tag links are short range, the system can recognize events in all areas within the deployment zone given sufficient coverage of tags.
4. Invariance w.r.t. to different deployment locations: Once the system is deployed and trained, it can be deployed in the same constellation in a totally different environment and will perform identically without requiring retraining.

5. EXPERIMENTAL RESULTS

5.1. Prototype Tag

The modular tag prototype that enables collection of the BCSI vector data for passive channel estimation and activity recognition has been fabricated [19]. The tag itself includes a single dipole antenna on a separate printed circuit board (PCB) and uses discrete component architectures for the modulator and demodulator implementation for tag-to-tag communication. The modulator design includes an RF switch which accommodates ten different reflection phases. The demodulator consists of a passive envelope detector followed by a low-pass filter. The control is implemented on a low-power microcontroller (TI MSP 430). For measurement of BCSI, the envelope detector output is connected to a PCB with high-resolution 16-bit 80 kbps ADC that enables data logging of the envelope signal and off-line computation of the BCSI vector. The exciter is implemented using a software radio BladeRF [20] and open source software [21]. The exciter emits a CW signal at 915 MHz. The BladeRF is connected to a 9 dBi circularly polarized antenna [22].

5.2. Experimental Setup

We have conducted an initial study in which we evaluated the proposed technique for activity recognition [19]. We have collected training and testing samples for 9 participants that performed 10 different daily activities in a lab setting. The activities are grouped into 8 classes: 1) brushing, 2) falling, 3) running, 4) no activity (person is either sitting or standing still), 5) sitting down from standing position, 6) standing up from seating position, 7) walking, 8) waving (person is either sitting or standing while waving). The outline of the used 9 m $\times$ 9 m room, along with the positions of the RF exciter, Tx tag and four Rx tags and the selected four positions of the subject performing the activity is shown in Fig. 3. The exciter power is set at 15 dBm and the transmitter transmits at different ten phases. The sampling time of the collection of BCSI information is 50 ms and the data is recorded for 2.5 s from the start of the activity. Each subject repeated 5 times each activity in each of the four depicted locations in Fig. 3.

5.3. Estimating A_B and θ_{BC}

Each activity is captured in a duration of 2.5 seconds using 50 transmissions. For each transmission, we have observations of the amplitudes for a set of fixed phases, from which a sinusoid function that is characterized by its phase and amplitude can be estimated with standard signal processing techniques. The resolution can be improved if we have more observations.

5.4. Invariance

Each activity experiment is encoded by the dynamics of the BCSI vector. In this subsection, we show that the information encoded, not only captures the signatures of different activities, but also is invariant w.r.t. location, changes in deployment environment and human subject. To better visualize the similarities, we only compare the dynamics of A_B since the similarities in the dynamics of θ_{BC} and ΔA_E need re-scaling, reversing and shifting to be seen.

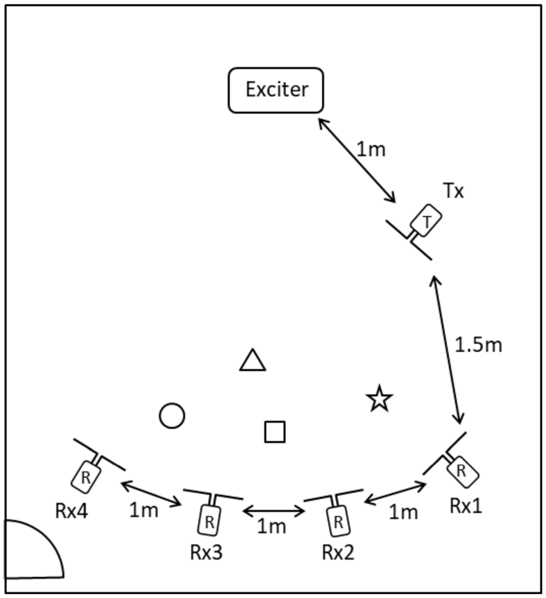

Fig. 3: The experimental setup for the activity recognition study showing the locations of the exciter and the tags.

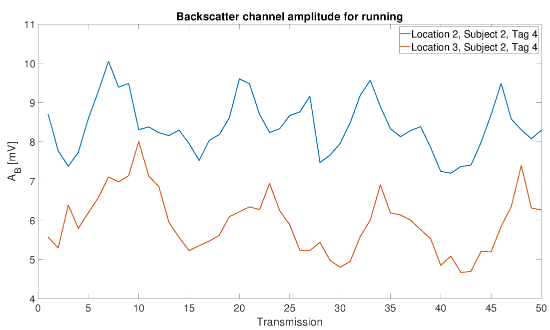

Fig. 4: Dynamic patterns of A_B in BCSI vectors from Rx tag 4. The same subject performed the activity of running at two different locations.

5.4.1. Invariance w.r.t. location

To demonstrate the invariance w.r.t to location, we show the dynamics of A_B from two BCSI vectors, in Fig. 4. Both were obtained from Rx tag 4, corresponding to a human subject performing the activity of running at two different locations, location 2 and location 3, respectively. It is clear that the waveforms captured by the tags at the two different locations are very similar.

5.4.2. Invariance w.r.t. changes in the deployment environment

To show the invariance in this case, we adopted BCSI vectors from two different Rx tags, tag 1 and tag 4, that correspond to the same subject that performed the activity of falling at two different locations, respectively. The dynamic patterns of the channel amplitude are shown in Fig. 5. Again, the similarity of the patterns is apparent.

5.4.3. Invariance w.r.t. to human subject

The invariance w.r.t. to human subjects is demonstrated in Fig. 6. An activity of walking was performed at the same location. We compared the amplitude from two BCSI vectors obtained from the same

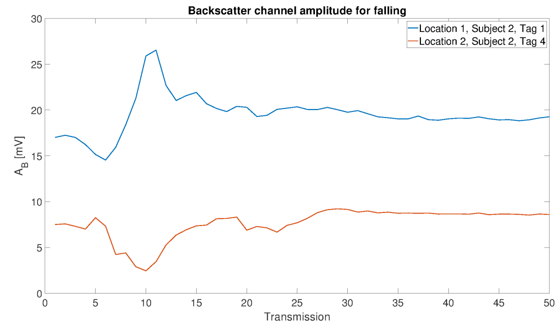

Fig. 5: Dynamic patterns of A_B in BCSI vectors from two different Rx tags. The same subject performed the activity of falling at two different locations.

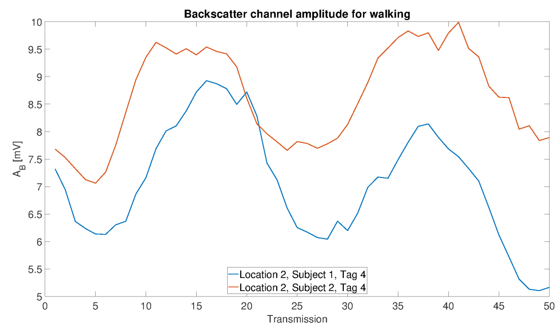

Fig. 6: Dynamic patterns of A_B in BCSI vectors from the same Rx tag. The different subjects performed the activity of walking at the same location.

Rx tag, one for subject 1 and the other for subject 2. It is obvious that the two waveforms are very similar. Intuitively, activity walking is similar to running but with a slower pace than running. Interestingly, after comparing Fig. 4, where activity running is used, and Fig. 6, we can see that this is also captured by the waveforms of the amplitude.

6. CONCLUSIONS

In this paper we address tag-to-tag networks, where passive RFID tags communicate with each other without the presence of RFID readers. For back-scattering, they either use local RF exciters or ambient RF signals. The tags for communication exploit multiphase probing, which in turn provides rich RF analytics about the environment where the tags operate. An important characteristic of the analytics is that they are invariant to a number of variables, including the deployment environment. We show the invariance from data acquired from our tags. RF analytics from a tag-to-tag network like ours will provide many opportunities for development of novel signal processing and machine learning methods for inference. The range of applications can be wide, and besides activity recognition, it will include monitoring of infrastructure such as bridges and buildings and enhancing the smartness of the spaces we live in.

7. ACKNOWLEDGMENT

This research was supported by the National Science Foundation under grant number CNS-1763843.

8. REFERENCES

[1] V. Liu, A. Parks, V. Talla, S. Gollakota, D. Wetherall, and J. R. Smith, "Ambient backscatter: wireless communication out of thin air," in *ACM SIGCOMM Computer Communication Review*, vol. 43, no. 4. ACM, 2013, pp. 39–50.

[2] B. Kellogg, A. Parks, S. Gollakota, J. R. Smith, and D. Wetherall, "Wi-fi backscatter: Internet connectivity for rf-powered devices," in *ACM SIGCOMM Computer Communication Review*, vol. 44, no. 4. ACM, 2014, pp. 607–618.

[3] A. N. Parks, A. Liu, S. Gollakota, and J. R. Smith, "Turbocharging ambient backscatter communication," *ACM SIGCOMM Computer Communication Review*, vol. 44, no. 4, pp. 619–630, 2015.

[4] P. V. Nikitin, S. Ramamurthy, R. Martinez, and K. Rao, "Passive tag-to-tag communication," in *RFID (RFID), 2012 IEEE International Conference on*. IEEE, 2012, pp. 177–184.

[5] G. Marrocco and S. Caizzone, "Electromagnetic models for passive tag-to-tag communications," *IEEE Transactions on Antennas and Propagation*, vol. 60, no. 11, pp. 5381–5389, 2012.

[6] C. Liu and Z. J. Haas, "Multi-hop routing protocols for rfid systems with tag-to-tag communication," in *Military Communications Conference (MILCOM), MILCOM 2017-2017 IEEE*. IEEE, 2017, pp. 563–568.

[7] Y. Karimi, A. Athalye, S. R. Das, P. M. Djurić, and M. Stanaćević, "Design of a backscatter-based tag-to-tag system," in *RFID (RFID), 2017 IEEE International Conference on*. IEEE, 2017, pp. 6–12.

[8] A. Athalye, J. Jian, Y. Karimi, S. R. Das, and P. M. Djurić, "Analog front end design for tags in backscatter-based tag-to-tag communication networks," in *Circuits and Systems (ISCAS), 2016 IEEE International Symposium on*. IEEE, 2016, pp. 2054–2057.

[9] M. Dowling, M. F. Bugallo, S. Das, and P. M. Djurić, "Tracking of objects in a passive backscattering tag-to-tag network," in *2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC)*. IEEE, 2018, pp. 1–5.

[10] J. Ryoo, Y. Karimi, A. Athalye, M. Stanaćević, S. Das, and P. Djurić, "Barnet: Towards activity recognition using passive backscattering tag-to-tag network," in *Proceedings of the 16th Annual International Conference on Mobile Systems, Applications, and Services*. ACM, 2018, pp. 414–427.

[11] K. Finkenzeller, *RFID Handbook: Fundamentals and Applications in Contactless Smart Cards and Identification*. New York, NY, USA: John Wiley & Sons, Inc., 2003.

[12] J. Griffin and G. Durgin, "Complete link budgets for backscatter-radio and rfid systems," *IEEE Trans. on Antennas and Propagation Magazine*, vol. 51, no. 2, pp. 11–25, 2009.

[13] C. Boyer and S. Roy, "Backscatter communication and rfid: Coding, energy, and mimo analysis," *IEEE Transactions on Communications*, vol. 62, no. 3, pp. 770–785, 2014.

[14] P. N. Alevizos and A. Bletsas, "Industrial swipt: Backscatter radio and rfids," *Wireless Information and Power Transfer: Theory and Practice*, pp. 61–79, 2018.

[15] C.-Y. Yao and W.-C. Hsia, "An indoor positioning system based on the dual-channel passive rfid technology," *IEEE Sensors Journal*, vol. 18, no. 11, pp. 4654–4663, 2018.

[16] F. Adib, Z. Kabelac, and D. Katabi, "Multi-person localization via rf body reflections." in *NSDI*, 2015, pp. 279–292.

[17] H. Li, C. Ye, and A. P. Sample, "IDSense: A human object interaction detection system based on passive UHF RFID," in *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 2015, pp. 2555–2564.

[18] S. Sigg, U. Blanke, and G. Troster, "The telepathic phone: Frictionless activity recognition from wifi-rssi," in *Pervasive Computing and Communications (PerCom), 2014 IEEE International Conference on*. IEEE, 2014, pp. 148–155.

[19] J. Ryoo, J. Jian, A. Athalye, S. R. Das, and M. Stanaćević, "Design and evaluation of bttn: A backscattering tag-to-tag network," *IEEE Internet of Things Journal*, 2018.

[20] "Bladerf: the usb 3.0 superspeed software defined radio." [Online]. Available: http://nuand.com/

[21] "Bladerf usb 3.0 superspeed software defined radio source code." [Online]. Available: https://nuand.com/forums/

[22] "902-928 mhz 9 dbic circular polarity panel." [Online]. Available: http://www. lairdtech.com/products/s9028pcl- s9028pcr