RFID Tag Acquisition via Compressed Sensing

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***Abstract*—We focus on simultaneously identifying a small subset of radio frequency identification tags out of a large known total set. This, for instance, applies to the popular use-case of a supermarket checkout where the items in a shopping cart need quick and reliable identification. Since the number of items in the cart is usually very small compared to the total amount of inventoried items in a store, it appears natural to formulate the identification problem according to compressed sensing, exploiting the inherent sparsity of the problem and allowing collisions in tag responses rather than avoiding them. This yields a very efficient way of identifying tags with only a small number of measurements. We introduce a novel tag identification scheme that utilizes the computationally cheap Approximate Message Passing (AMP) algorithm. A simulation-based heuristic is introduced to minimize the number of required measurements for AMP recovery. Furthermore, a method of implementation is sketched, and the performance of the proposed scheme is investigated and compared to the well known frame slotted aloha protocol. A large gain in identification throughput is achieved.**

I. Introduction

Radio Frequency Identification (RFID) constitutes a ubiquitous technology that carries a wide range of applications. This is enabled by cheap (passive) tag designs that can be printed on objects of interest such as groceries, books and clothes, to name just very few areas of application. When these tags are placed close enough to a reader device, i.e., within the so-called read range, they are powered up by the field emitted by the reader and respond according to the implemented protocol.

The crux in many tag acquisition systems emerges from the fact that if several tags are put in read range simultaneously, their responses superpose at the reader and thereby produce collisions. To mitigate this problem, many approaches have been studied in literature, the most prominent ones being collision avoidance protocols as subsumed in [1], [2]. A widely used scheme is Frame Slotted ALOHA (FSA) that introduces a frame structure composed of several time slots. Each tag in read range randomly selects one of these slots to transmit its data, which avoids collisions up to a certain probability. Note that only collision-free slots, i.e., slots containing a single tag response, can be decoded in the basic form of FSA. In [3], a physical layer collision recovery scheme was proposed which is able to recover from collisions by separating the superposed tag responses in the I/Q-plane by using a single antenna at the reader on the one hand, or by utilizing multiple antennas to exploit the spatial signatures for collision recovery on the other hand. The work on spatial collision recovery on top of FSA was continued in [4], [5], where a so called postpreamble for channel estimation was introduced upon the standard compliant protocol [6]. The proposed scheme is able to recover from up to eight collisions in a slot utilizing four receive antennas at the reader.

In this paper, we break the mold and introduce a scheme where collisions are regarded as beneficial rather than destructive, which yields large gains in identification throughput. This, however, requires an alteration of the existing standard [6]. Furthermore, the tag responses for identification have to be designed according to a certain rule, and all possible responses have to be known by the reader. The scheme thus applies to applications such as a store or a library where the inventory, equipped with tags, is known in advance. We formulate the identification problem in terms of compressed sensing [7], a sampling theory that allows to acquire a sparsely populated data vector by considerably fewer measurements than the vector dimension (undersampling). Up to now, only few publications connect RFID with compressed sensing theory. In [8], collisions are regarded as a sparse code which can be decoded by compressed sensing. The scheme proposed in [9] utilizes the sparsity in inventory tracking; the objects that are subject to change resemble a sparse subset of the total inventory set. Our approach exploits sparsity that arises from the fact that only a few tags out of all possible tags are activated (e.g. in read range) at a given time.

The remainder of this paper is organized as follows. Section II subsumes the basics of compressed sensing theory and introduces one method of recovery that utilizes the computationally cheap Approximate Message Passing (AMP) algorithm. Section III then introduces the underlying problem scenario, the physical model and the problem formulation in terms of compressed sensing. In Section IV, we adopt a heuristic approach in order to find the minimal number of required measurements for recovery. This approach is general and not restricted to the RFID scenario. After these preparations, Section V deals with the actual implementation of the scheme and explains the procedure required to reliably recover all activated tags. Finally, simulation results are presented and the performance is compared to FSA. Section VI concludes the paper.

978-1-4799-4680-8/14/$31.00 ©2014 IEEE

II. Compressed Sensing in a Nutshell

Compressed sensing [7] aims at reconstructing a high-dimensional signal vector $\mathbf{x} \in \mathbb{C}^N$ from $M < N$ non-adaptive linear measurements

$$\mathbf{y} = \mathbf{A}\mathbf{x} + \mathbf{w}, \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^M$ is the measurement vector, $\mathbf{A} \in \mathbb{R}^{M\times N}$ is the sensing matrix that describes the measurements and $\mathbf{w} \in \mathbb{C}^M$ is additive measurement noise. If $\mathbf{x}$ exhibits sparsity, i.e., only few elements in $\mathbf{x}$ are non-zero, it can be recovered despite (1) being an underdetermined system of linear equations. The vector $\mathbf{x}$ is henceforth assumed to be K-sparse, it has at most K out of N non-zero entries, where $K \ll N$. To ensure stable recovery from noisy measurements, the sensing matrix $\mathbf{A}$ has to satisfy the Restricted Isometry Property (RIP) [10] $(1-\delta_S)\|\mathbf{v}\|_2^2 \leq \|\mathbf{A}\mathbf{v}\|_2^2 \leq (1+\delta_S)\|\mathbf{v}\|_2^2$ for all K-sparse vectors $\mathbf{v}$, which basically implies that $\mathbf{A}$ preserves their Euclidean length up to a small constant defined by δ_S. Appropriate sensing matrices can be constructed deterministically as proposed in [11], which usually imposes a constraint on the number of measurements M. A simple yet effective way is to pick $\mathbf{A}$ randomly with i.i.d. Gaussian entries or Rademacher[1] distributed entries. Such matrices were proven in [12] to almost surely satisfy the RIP while the number of required measurements for successful recovery is lower bounded by[2]

$$M = cK \log \frac{N}{K}. \tag{2}$$

The recovery of $\mathbf{x}$ from (1) can be formulated according to the so called Least Absolute Shrinkage and Selection Operator (LASSO) [13], also known as basis pursuit denoising, which yields a non-linear convex optimization problem that reads

$$\widehat{\mathbf{x}} = \arg\min_{\widetilde{\mathbf{x}}} \left\{ \frac{1}{2}\|\mathbf{y} - \mathbf{A}\widetilde{\mathbf{x}}\|_2^2 + \lambda \|\widetilde{\mathbf{x}}\|_1 \right\}. \tag{3}$$

The underlying intuition is to find the most accurate solution with the smallest support (motivated by the assumed sparsity of $\mathbf{x}$), where λ allows a trade-off between accuracy with respect to the observation error $\|\mathbf{y} - \mathbf{A}\widetilde{\mathbf{x}}\|_2^2$ and the sparsity[3] of the solution $\|\widetilde{\mathbf{x}}\|_1$. The proper choice of λ will be subject of Section IV-A.

Many schemes [14] have been proposed to solve the LASSO problem. The Approximate Message Passing (AMP) algorithm introduced in [15] constitutes a low complexity iterative approach with fast convergence, well suited for practical implementations of compressed sensing which makes it our method of choice.

III. RFID Scenario and Recovery Formulation

Let us now consider the physical scenario in which we want to identify K activated tags out of a large total number of N tags. The set of all tags is denoted $\mathcal{T} = \{1, ..., n, ..., N\}$, it has cardinality $|\mathcal{T}| = N$ and could correspond to all possible items in a store. The subset of activated tags that we wish to identify is $\mathcal{T}_\text{A} = \{a_1, ..., a_k, ..., a_K\} \subset \mathcal{T}$, it has cardinality $|\mathcal{T}_\text{A}| = K$ and could e.g. resemble all tags in the read-range of the RFID reader. The setup is illustrated in Figure 1.

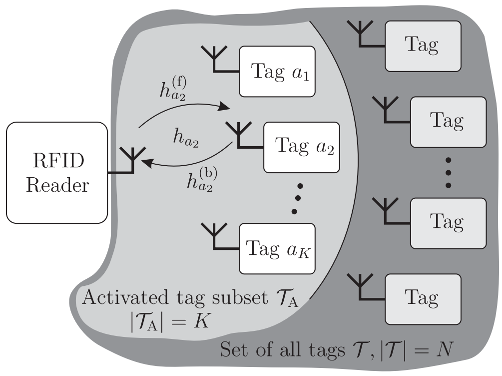

Fig. 1. Illustration of the problem scenario: $\mathcal{T}_\text{A}$ denotes the set of activated tags that are to be identified by the reader.

A. Tag Specification and Channel Model

We assume passive tags that are powered by the continuous-wave signal emitted by the reader. Backscatter modulation [16] is used to convey information in the uplink from tag to reader. To this end, a tag modulates its load resistor, which in turn modulates the reflection coefficient of its antenna. This basically generates an Amplitude Shift Keying (ASK) signal as a tag response. The two resulting ASK symbol levels are henceforth denoted $b_0 \in \mathbb{R}$ and $b_1 \in \mathbb{R}$ corresponding to binary 0 and binary 1, respectively.

Since backscatter communication with low rate yields narrow band transmissions [8], the individual physical channels can be described by a complex coefficient (one tap channel) that models amplitude and phase change. We assume a dyadic channel as suggested in [3], [16] that consists of a forward channel from reader to tag and a backward channel from tag to reader. As we consider static multi-path channels, the magnitudes of the forward and backward channels are assumed to be Rayleigh distributed. A channel coefficient for the forward or backward channel of tag n is thus drawn from a complex normal distribution with zero mean and unit variance. The total channel from reader to tag n and back is

$$h_n = h_n^{(\text{f})} h_n^{(\text{b})}. \tag{4}$$

B. Tag Identification with Compressed Sensing

We now merge the compressed sensing theory from Section II with the practical application of RFID tag identification. To this end, we aim at formulating the tag interrogation in terms of (1). Consider the following properties:

- Each tag $n \in \mathcal{T}$ possesses a unique length M signature that is arranged in a vector $\mathbf{s}_n \in \{b_0, b_1\}^M$. The sequences are generated pseudo-randomly with $P\{b_0\} = P\{b_1\} = 0.5$, i.e., both ASK symbols occur with equal probability.

[1] Entries are $\{-1, 1\}$ with equal probability.

[2] $c \in \mathbb{R}$ is a small constant.

[3] Sparsity is usually expressed by the l_0-"norm" according to $\|\mathbf{x}\|_0 \leq K$. The l_1-norm relaxation was proven in [7] to yield the same result in high dimensions while introducing a favorable convex optimization problem.

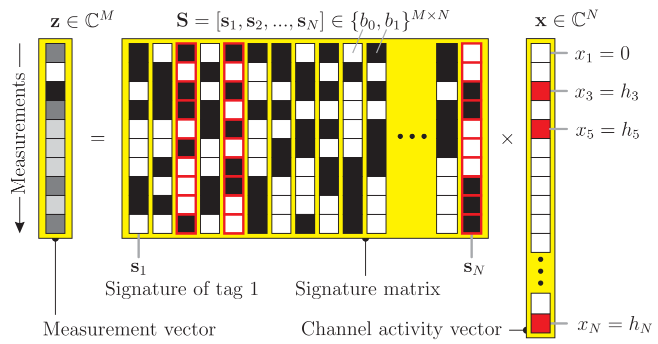

Fig. 2. Measurement process according to (5), noise omitted. Activated tag signatures selected by the non-zero elements in $\mathbf{x}$ are highlighted.

- The N aforementioned signature sequences form the columns of the signature matrix $\mathbf{S} = [\mathbf{s}_1, ..., \mathbf{s}_N] \in \{b_0, b_1\}^{M\times N}$. The reader knows all signatures and thereby $\mathbf{S}$.
- The activated tag subset $\mathcal{T}_\text{A}$ constitutes the support of the K-sparse channel activity vector $\mathbf{x} \in \mathbb{C}^N$. Its K nonzero entries, located at indices $n = \mathcal{T}_\text{A}$, correspond to the channel coefficients of the activated tags, see (4).
- Additive white measurement noise $\mathbf{w} \in \mathbb{C}^M$ is assumed at the reader. Its entries are drawn from a circularly symmetric complex normal distribution with zero mean and variance σ_w^2.
- Perfect synchronization is assumed in this first approach to the topic. Activated tags respond concurrently with constant symbol duration.

The reader starts the tag interrogation with a query command, and all activated tags respond simultaneously with their unique signature. This constitutes a measurement process where each measurement entails one symbol transmission, it is illustrated in Figure 2 and formulated as

$$\mathbf{z} = \mathbf{S}\mathbf{x} + \mathbf{w}, \tag{5}$$

where the measurement vector $\mathbf{z} \in \mathbb{C}^M$ stores the noisy superposition of all activated tag responses which are selected by the K non-zero elements in $\mathbf{x}$. (5) already looks very similar to (1). In order to perform stable recovery with AMP, the signature matrix $\mathbf{S}$ should exhibit zero mean columns [14]. Remember that all columns (signatures) in $\mathbf{S}$ are composed of the same ASK symbols b_0 and b_1, and both symbols occur equally often. All columns therefore have the same mean $\bar{b} = (b_0 + b_1)/2$. An equivalent and AMP compliant formulation of the measurement is obtained by

$$\mathbf{y} = \mathbf{z} - \text{mean}(\mathbf{z}) = \mathbf{A}\mathbf{x} + \mathbf{w}, \tag{6}$$

where $\mathbf{A} \in \{-\bar{b}, \bar{b}\}$ is a valid sensing matrix since its entries obey the Rademacher distribution (up to a factor) and it thus almost surely satisfies the RIP. Finally, its columns are normalized to have unit l_2-norm, another requirement of the iterative AMP algorithm. We use Algorithm 1 for recovery, where $\eta_\tau(.)$ performs soft thresholding with threshold τ. The iterations are stopped if the residual $\mathbf{r}^t$ does not change notably anymore (controlled by a small constant ϵ) or t_max is reached.

Algorithm 1 Approximate Message Passing (AMP) [15]

initialize $\mathbf{r}^t = \mathbf{y}$ and $\mathbf{x}^t = \mathbf{0}$ for $t = 0$
do
  $t = t + 1$ ▷ advance iterations
  $\tau = \frac{\lambda}{\sqrt{M}} \left\|\mathbf{r}^{t-1}\right\|_2$ ▷ compute threshold
  $\mathbf{x}^t = \eta_\tau(\mathbf{x}^{t-1} + \mathbf{A}^\text{T}\mathbf{r}^{t-1})$ ▷ soft thresholding
  $b = \frac{1}{M}\left\|\mathbf{x}^t\right\|_0$ ▷ compute sparsity
  $\mathbf{r}^t = \mathbf{y} - \mathbf{A}\mathbf{x}^t + b\mathbf{r}^{t-1}$ ▷ compute residual
while $\left\|\mathbf{r}^t - \mathbf{r}^{t-1}\right\|_2 > \epsilon$ and $t < t_\text{max}$
return $\widehat{\mathbf{x}} = \mathbf{x}^t$ ▷ recovered sparse vector

IV. AMP Tuning

In this section, we search for the minimal number of measurements M required to recover $\mathbf{x}$ from (6). (2) states the basic dependency of M on the number of activated tags K (sparsity) and the entire tag population N. The factor c mainly depends on the Signal to Noise Ratio (SNR) and the chosen trade-off between measurement accuracy and sparsity, λ. The SNR is defined as

$$\text{SNR} = \frac{\|\mathbf{A}\mathbf{x}\|_2^2}{M\sigma_w^2} = \frac{P}{\sigma_w^2}, \tag{7}$$

where $P = \|\mathbf{A}\mathbf{x}\|_2^2/M$ denotes the average signal power per measurement, which corresponds to the average backscattered signal power per bit in the considered RFID scenario. In order to maintain generality in this section, $\mathbf{x}$ is regarded as sparse random vector whose K non-zero entries are drawn from a complex normal distribution with zero mean and unit variance. $\mathbf{A}$ has i.i.d. Rademacher distributed entries.

As a performance measure, we introduce the Mean Squared Error (MSE) between the true vector $\mathbf{x}$ and its AMP recovery $\widehat{\mathbf{x}}$

$$\text{MSE} = \frac{1}{N}\|\widehat{\mathbf{x}} - \mathbf{x}\|_2^2 = \frac{1}{N}\sum_{n=1}^{N}|\widehat{x}_n - x_n|^2. \tag{8}$$

Aided by simulations, we now formulate a heuristic for the optimal choice of λ and the required number of measurements.

A. Optimal λ Selection

In [17], it was shown for the asymptotic setting[4] that the sparsity K is a decreasing function of λ, and that the MSE is a quasi-convex function of λ. This already gives a good intuition of what to expect.

Simulation results for determining the optimal λ are shown in Figure 3. The left plot (a) shows the MSE vs. λ for two SNR realizations and for variable M. Increasing the SNR reduces the overall MSE, increasing the number of measurements M (or equivalently factor c) reduces the MSE as well. We conclude:

- The MSE is a convex function of λ.
- Its minimum is attained at λ_o and does not depend on SNR or M, as long as SNR and M are sufficiently large for recovery to work.

[4] Asymptotic setting: $M \to \infty, N \to \infty$ while $M/N = \text{const.}$

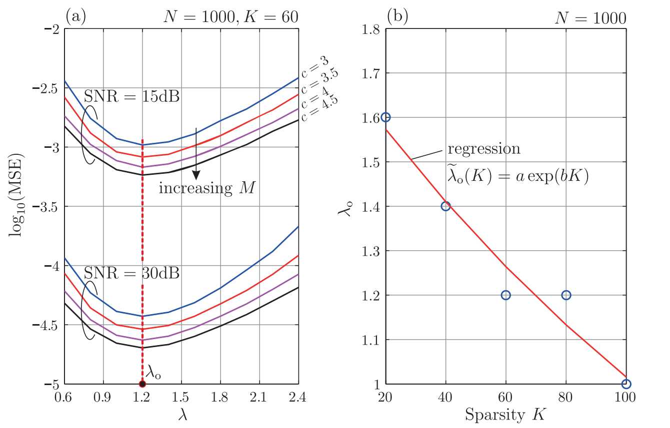

Fig. 3. (a) shows the MSE vs. λ. Note the convexity and the unique minimum at λ_o. (b) depicts the optimal value λ_o versus increasing K.

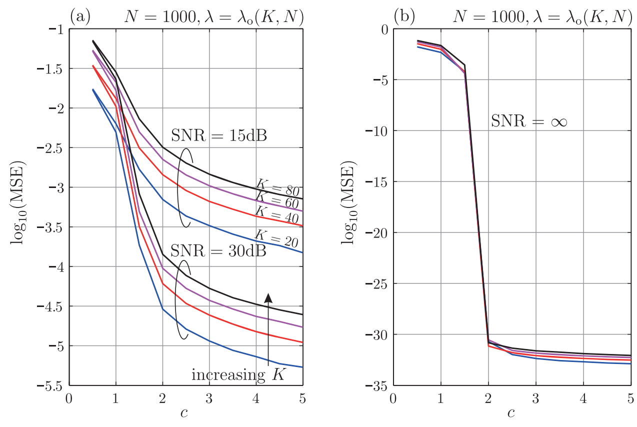

Fig. 4. (a) visualizes the MSE vs. c for various values of K and SNR. Remember that c determines the number of measurements according to (2). (b) depicts the MSE vs. c in the noiseless case. Note the distinctive threshold of c where the MSE becomes numerically zero.

Note that increasing the problem dimension N while keeping K constant leads to an increased λ_o (not shown here), because $\mathbf{x}$ becomes more sparse compared to the total dimension N. The choice of the optimal value λ_o can thus be formulated as

$$\lambda_\text{o}(K, N) = \arg\min_{\lambda} \text{MSE}(\lambda, K, N). \tag{9}$$

The right plot (b) in Figure 3 displays λ_o versus K found by simulation. The red line depicts a regression $\widetilde{\lambda}_\text{o}(K) \approx 0.56 \exp(-5.5 \cdot 10^{-3} K)$ motivated by *Fig. 3* in [17].

B. Required Number of Measurements M

Now that we know how to select the trade-off between sparsity and measurement accuracy λ, we advance to the proper choice of the number of measurements M by studying the impact of the factor c in (2). Figure 4 illustrates its impact on the MSE for various SNRs and choices of K. We observe the emergence of a step in MSE that becomes more pronounced with increasing SNR. Furthermore, the MSE grows with increasing K, which is expected since reducing sparsity and increasing the number of nonzero values in $\mathbf{x}$ makes the recovery more prone to error.

For the noiseless case, i.e., SNR $= \infty$, the MSE becomes numerically zero at $c \geq 2$. Note that this is no general rule as larger K values than the plotted ones tend to require more measurements. We conclude:

- The MSE is a strictly monotonic decreasing function of c (equivalently of $M = cK \log(N/K)$).
- There exists a threshold for c above which the MSE decreases only slowly with further measurements.

For the considered values of K, the measurement multiplier c should be chosen $c \geq 2$ judging from Figure 4 (b). In Section V-C, we will consider the values $c = \{2, 3\}$ and investigate their impact on the identification throughput.

V. Implementation and Results

In the following, we assume an idealized scenario where the only physical impairments are the channel and the noise. The number of activated tags K is assumed to be known in advance, one method of its estimation is presented in [8]. Bit encoding with FM0 or Miller [6] and preambles are omitted.

A. Compressed Sensing Identification Algorithm

We now discuss one possible implementation of the proposed compressed sensing tag acquisition scheme. In the considered scenario, the purpose of tag acquisition is identification of activated tags with an optional read out of information, e.g. sensor data. The required (dynamic-)length M signature of each tag is generated by a pseudo-random generator that is seeded with the tag index n. These signatures can easily be generated at the reader as well, the ensemble of all signatures constitutes the signature matrix $\mathbf{S}$.

The acquisition of all activated tags happens in one or more identification cycles, a single cycle is depicted in Figure 5. A cycle starts with the reader initiating the identification process using the SIGNATURE QUERY command. This command also includes the signature length (number of measurements) M for the current cycle, chosen according to a prior K and SNR estimation. The tags simultaneously respond with their signatures which triggers the measurement process from (5). After receiving $\mathbf{z}$, the reader recovers $\mathbf{x}$ from (6) utilizing AMP. It then estimates the set of activated tags $\mathcal{T}_\text{A}$ by considering only the K strongest components in $\widehat{\mathbf{x}}$. The corresponding indices are collected in the estimated set of activated tags $\widehat{\mathcal{T}}_\text{A} = \{\widehat{a}_1, ..., \widehat{a}_K\}$. In case of non-perfect recovery due to low SNR or insufficient number of measurements, false detections occur which implies that there are more than K non-zero values in $\widehat{\mathbf{x}}$. If large enough, these false detections appear in the set of the K largest values in $\widehat{\mathbf{x}}$ and supersede the true values, which generates a faulty estimated set of activated tags. In Figure 5, $\widehat{a}_2$ represents such a false detection. To ensure correct tag identification, the reader has to enquire all the tags in $\widehat{\mathcal{T}}_\text{A}$. The correctly found tags respond with a simple ACK response or by transmitting their optional data payload. After a successful enquiry, a tag will be silent and is no longer an element of $\mathcal{T}_\text{A}$. False detections are not contained in the true set of activated tags $\mathcal{T}_\text{A}$ and therefore produce no response, the reader continues enquiring after a timeout. The identification cycle has to be repeated on a reduced set of activated tags

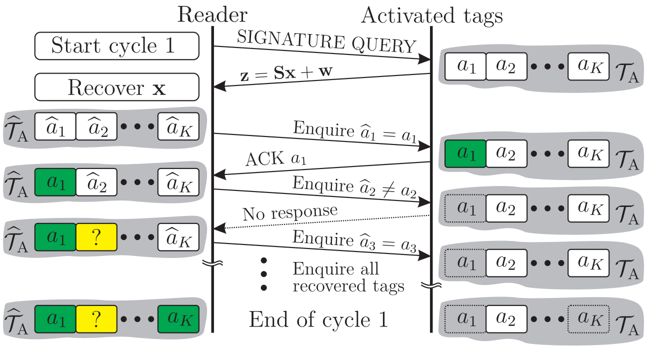

Fig. 5. Illustration of one identification cycle. Tag a_2 was missed and has to be detected in a successive cycle.

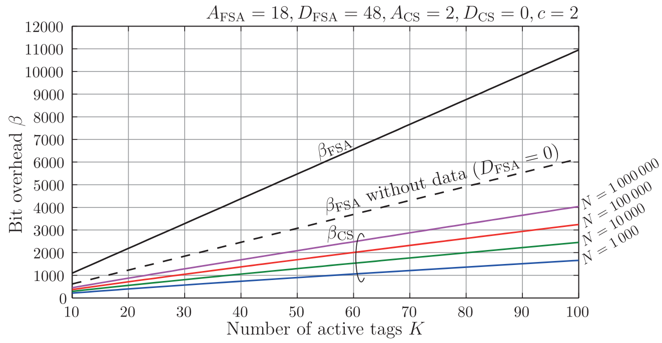

Fig. 6. Theoretically optimal (lowest possible) bit overhead for FSA (see (11)) and compressed sensing (see (10)) at infinite SNR.

(only unacknowledged ones) until all tags are detected and hence $\mathcal{T}_A = \{\emptyset\}$.

Let us investigate the overhead in bits required to successfully identify all tags. Since every tag knows its index $n \in \mathcal{T}$, an enquiry could contain the tag index $n = \hat{a}_k$ in binary representation and would therefore require $E = \lceil \log_2(N) \rceil$ bits. The ACK response can be very simple and might contain $A_{CS} = 2$ bits. If additional information is to be read out (e.g. sensor data), a data payload of length D_{CS} can be added to the ACK response. This is not the case in the considered identification-only scenario, thus $D_{CS} = 0$.

In the noiseless (SNR $= \infty$) case, one identification cycle suffices to recover the correct set of activated tags $\mathcal{T}_A$. The overhead in bits of one successful cycle in which all tags are recovered correctly reads

$$\begin{aligned} \beta_{CS} &= \underbrace{M}_{\text{Identification}} + \underbrace{K(E + A_{CS} + D_{CS})}_{\text{Enquiry, ACK and optional data}} \\ &\approx (\tilde{c}\log(N) - c\log(K) + A_{CS} + D_{CS})K, \end{aligned} \tag{10}$$

where the approximation is induced by neglecting the ceiling operation $\lceil . \rceil$ in $E = \lceil \log_2(N) \rceil$, M was substituted according to (2) and $\tilde{c} = c + 1/\log(2)$.

B. Frame Slotted Aloha for Comparison

The systematic difference between FSA [6] and the proposed compressed sensing based scheme is that FSA does not need to know the inventory in advance. The activated tags randomly choose a slot in a frame of size K (the optimal frame size corresponds to the number of activated tags [4]) in which they transmit a 16 bit random number (RN16). The reader acknowledges a tag in a collision-free slot by transmitting an echo of its RN16 number, the addressed tag then transmits its payload. Colliding tags are scheduled for a new frame.

The overhead in bits for the tag acquisition in one frame (at SNR $= \infty$) can be written

$$\beta_{FSA} = \underbrace{\frac{16}{0.368}}_{\text{Identification}} K + \underbrace{K(A_{FSA} + D_{FSA})}_{\text{ACK and data}} \approx 109.48K, \tag{11}$$

where $\frac{16}{0.368}K$ corresponds to the RN16 sequences in all K slots assuming an optimal throughput (coincides with the probability of choosing a collision free slot) of 0.368 tags per slot [3] achievable at infinite SNR, $A_{FSA} = 18$ bit consists of 2 bit ACK command overhead [6] plus RN16 echo to acknowledge the slots, and $D_{FSA} = 48$ bit is the data payload assumed to contain PC, EPC and CRC16 (see [6] for details). Not knowing the inventory in advance requires to read out the data payload (e.g. product code), which is not required in the compressed sensing approach.

Comparing (10) with (11), it is evident that the total tag population N affects the identification throughput of the compressed sensing scheme but not of the FSA scheme. Figure 6 depicts the optimal bit overhead for FSA and compressed sensing achieved at SNR $= \infty$. Since proposed compressed sensing approach exhibits a lower bit overhead, it is expected to achieve an improved identification throughput over FSA. This is true as long as N is below $N \approx 10^{15}$ tags where both overheads are about equal.

Note that both bit overhead formulas apply to the noiseless case and constitute a lower bound. The lower the SNR, the more cycles are needed in the compressed sensing scheme and the more frames are needed in the FSA scheme. Let us now investigate the real application case with finite SNR.

C. Simulation Results

In this section, the identification part of (10) and (11) is impaired by noise. The subsequent enquiry, acknowledgement and data read-out is assumed to work perfectly. The results are averaged over 800 realizations.

The bit overhead of FSA is adapted for each SNR value according to $\beta_{FSA}(\text{SNR}) = \frac{16}{\text{Tps(SNR)}}K + K(A_{FSA} + D_{FSA})$, where Tps is the throughput in tags per slot of standard FSA without collision recovery capabilities and a reader that utilizes a minimum mean squared error receiver. Please refer to [5] for details. The bit overhead of compressed sensing β_{CS} is generated by accumulating the bits of all necessary identification cycles until all tags are identified correctly.

Figure 7 shows a bit overhead comparison for various SNRs. We observe an increasing bit overhead for shrinking SNR as expected, and compressed sensing clearly outperforms FSA by producing a substantially lower bit overhead.

Finally, the identification throughput measured in tags per bit is defined as $T = K/\beta$. Figure 8 illustrates an identification throughput comparison. The proposed compressed sensing

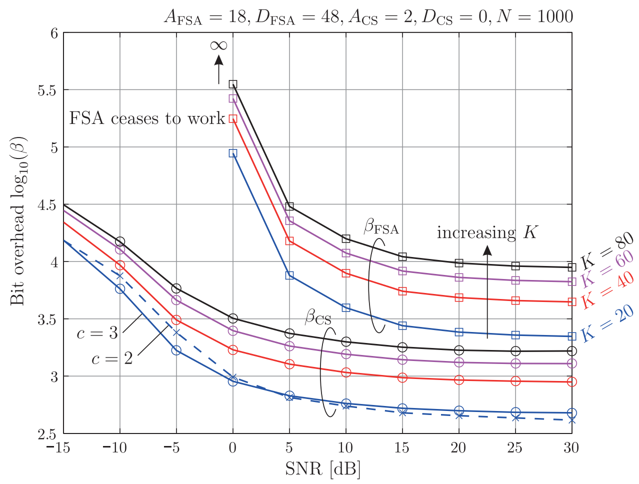

Fig. 7. Comparison of bit overhead vs. SNR.

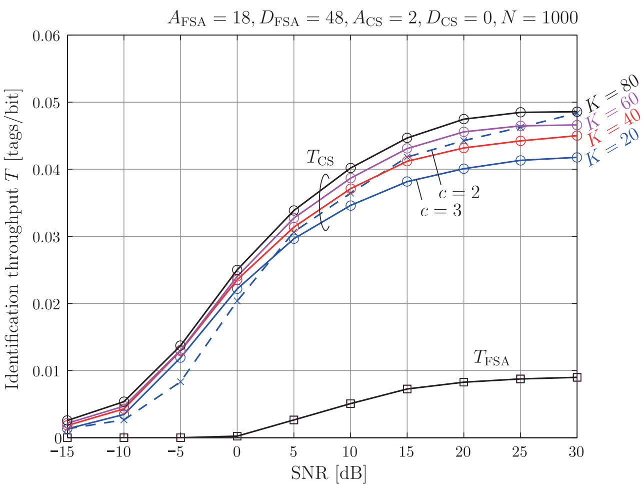

Fig. 8. Comparison of identification throughput vs. SNR.

based scheme clearly outperforms FSA, especially at low SNR where FSA does not work at all. While the throughput of FSA is independent of the number of activated tags K, the compressed sensing based scheme exhibits a dependency.

The measurement multiplier was generally chosen to be $c = 3$. The dashed lines depict the results for $c = 2$ (only drawn for $K = 20$). Increasing c implies a larger number of measurements M per cycle. At high SNR, a $c > 2$ decreases throughput since $c = 2$ already achieves perfect recovery (see Figure 4 (b)) in very few identification cycles, in particular one cycle at SNR $= \infty$. At low SNR, increasing c leads to higher throughput since the recovery quality improves with additional measurements, and fewer identification cycles are needed. For optimal performance, the choice of c can be made SNR and K dependent.

VI. Conclusion

We provided a method for selecting the accuracy–sparsity trade-off λ and the number of required measurements M for AMP recovery based on MSE investigations. We then proposed an algorithmic implementation of an RFID tag identification scheme based on compressed sensing utilizing AMP for recovery. Proposed approach exhibits a large gain in identification throughput over the widely used FSA protocol. It was demonstrated to work reliably even in the low SNR regime where FSA ceases to work.

Acknowledgment

This work has been funded by the Christian Doppler Laboratory for Wireless Technologies for Sustainable Mobility, and its industrial partner Infineon Technologies. The financial support by the Federal Ministry of Economy, Family and Youth and the National Foundation for Research, Technology and Development is gratefully acknowledged. We finally like to thank C. Mecklenbräuker, M. Rupp and R. Langwieser for their fruitful discussions and stimulative thoughts.

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