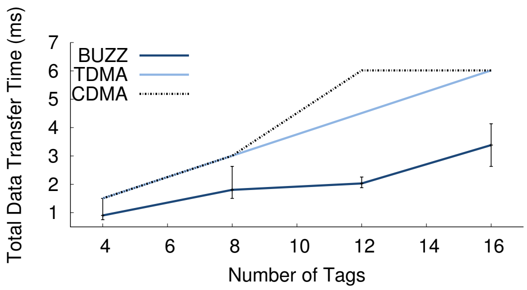

Figure 10—Total data transfer time: Buzz achieves 2× improvement in total transfer time over TDMA and CDMA. Unlike TDMA and CDMA which have a fixed rate of 1 bit/symbol, the rateless nature of Buzz allows it to adapt to an average rate of 2 bits/symbol.

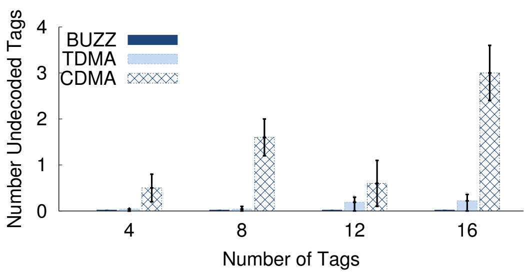

Figure 11—Message errors: CDMA has the lowest reliability. TDMA has few errors because it uses Miller-4 code. Buzz's bars are not visible because it has zero errors due to its rateless code.

to a 2× increase in aggregate bit rate of the network. However, this statistic understates the efficiency gain Buzz brings about. Unlike Buzz, TDMA and CDMA do not adapt their rates, and therefore might have decoding errors upon the completion of all the nodes' transmissions. These decoding errors lead to retransmissions, further reducing their efficiency.

Message Reliability: Commercial backscatter systems use a checksum to decide whether a message is decoded correctly and send a NAK if the checksum does not pass [14]. Thus, the number of messages decoded incorrectly represents a lower bound of retransmissions needed. Fig. 11 shows the number of tags whose messages were not correctly decoded for the same traces in Fig. 10.

Due to its automatic rate adaptation, Buzz decodes all messages correctly. TDMA has very few errors because it uses Miller-4 code which increases its robustness to bad channels. CDMA is less reliable, and as the number of tags in the network increases, its reliability quickly degrades. This is mainly because all tags get equal shares of the channel in CDMA, despite the fact that there is generally a disparity in channel quality between them. Note that in Fig. 11, CDMA for $K = 12$ has fewer undecoded messages than both $K = 8$ and $K = 16$. The reason for this is that we let each of the twelve tags use unique Walsh code of 16 bits, as no Walsh code of 12 bits is available [30]. This implies that one could use a longer code to increase reliability in CDMA, however, this comes at the expense of efficiency.

Next, we focus on more challenging channel conditions to further investigate the reliability of Buzz and TDMA. In this experiment, we use four tags and keep moving the tags further and further away from the reader to worsen the channels of all tags. Fig. 12 shows the comparison between Buzz and TDMA. When the channel quality in the network is good, Buzz decodes all four tags' messages correctly in a single time slot (4 bits/symbol), while TDMA requires 4 time slots to decode. As the channel worsens, TDMA starts failing to

a set of orthogonal Walsh codes of length 12 [30]. So instead, for $K = 12$ we use the orthogonal Walsh codes of length 16.

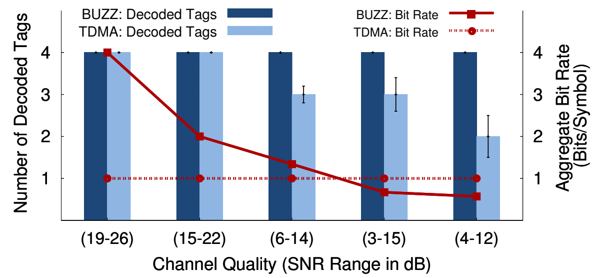

Figure 12—Under challenging conditions where TDMA experiences 50% (median) of message loss, Buzz adapts the bit rate to below 1 bit/symbol to match the channel quality and is able to decode with zero errors.

decode while Buzz gradually adapts the aggregate bit rate to below 1 bit/symbol. Notably, in the most challenging channel conditions, TDMA decodes two tags' messages incorrectly out of four, experiencing a 50% message loss rate. It is worth noting that for the same tag placement, CDMA has a message loss rate of 100%. In contrast, Buzz adapts the aggregate bit rate of the network to 0.57 bits/symbol, taking seven time slots to correctly decode all tags' messages. This demonstrates Buzz's ability to adapt to a bit rate of below 1 bit/symbol under challenging channel conditions, which is important for improving reliability of backscatter systems.

Power Efficiency: We investigate Buzz's impact on energy consumption of the backscatter nodes, and compare it to TDMA and CDMA. Backscatter energy consumption however is ultra-low, and therefore if we measure it after individual message transmission, the measurement noise may potentially exceed the consumed energy. Thus, to obtain robust measurements, we make each scheme reply to a large number of queries from the reader and measure the total energy consumption. The Moo has a small capacitor, leaving us unable to measure this accumulative energy consumption. As a workaround, we attach a large capacitor ($C = 0.1F$) to the Moo so that it can store enough energy in advance for our experiment.

In each experiment, the USRP reader sends a sequence of 8800 queries spaced by 10.2 ms to $K = 8$ tags.[8] Upon receiving each query, each tag wakes up and replies its message using the three schemes. We measure the energy consumed by the transfer as:

$$E_{consumed} = \frac{1}{2}CV_0^2 - \frac{1}{2}CV_f^2, \tag{10}$$

where V_0 is the voltage on the backscatter node's capacitor before the transfer and V_f is the voltage at the end of the transfer. We measure $E_{consumed}$ for three different values of V_0 since the amount of energy spent by a node depends on its initial voltage. For each value of V_0, we repeat the experiment for ten different positions of the tags and reader. At each position, we run the schemes one after another without changing the environment.

Fig. 13 shows the average net energy consumption for a single run (averaged by 8800) across tags and positions. As expected, each tag transmits for a much longer time in CDMA, and hence consumes more energy. In contrast, independent of the starting voltage V_0, Buzz does not consume much more energy than TDMA. There are two primary reasons for this. First, the rateless code in Buzz is sparse. Each node only transmits its message for very few times. Second, although in TDMA each node transmits its message

[8]Backscatter nodes continue to harvest energy from the reader's RF signal even while they drain energy performing the operations of the three schemes. To ensure a fair comparison, we keep the duration of the reader's continuous waveform the same between queries for all three schemes.

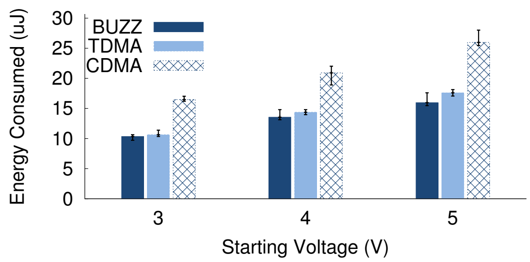

Figure 13—Energy consumption: Buzz does not consume much more energy than TDMA. Both Buzz and TDMA are significantly more energy efficient than CDMA.

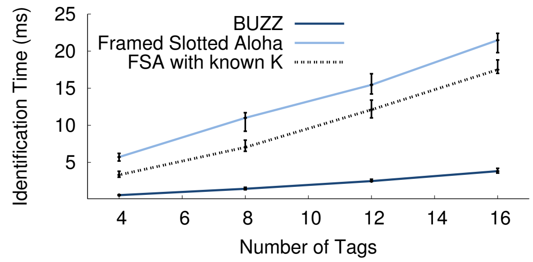

Figure 14—Identification time: Compared to Framed Slotted Aloha used in commercial RFID solutions, Buzz is significantly more efficient in identifying the nodes that want to transmit. Using the estimate of K from Stage 1 of Buzz's identification protocol improves the efficiency of Framed Slotted Aloha by 20%-40%.

only once, TDMA uses Miller-4 codes to protect the messages as recommended and hence has to switch the impedance on the antenna at 8 times of the data rate, which consumes more energy. If TDMA did not use Miller-4, it would lose its robustness and experience higher error rates [7]. Consequently, Buzz does not incur additional energy overhead to improve the efficiency and reliability of backscatter systems.

10. IDENTIFYING THE BACKSCATTER NODES

Recall that Buzz's node identification protocol consists of three stages: 1) estimating the number of backscatter nodes with data, 2) reducing the scale of the compressive sensing problem, and 3) compressive sensing decoding. In this section, we compare the efficiency of Buzz's three-step protocol with two baselines.

- **Framed Slotted Aloha (FSA):** This is the scheme adopted in the EPC Gen-2 standard [14]. Here, the reader initiates the identification phase by sending a query and allocating 2^Q time slots. Each tag picks a random slot and transmits a 16-bit random number (RN16), which serves as its temporary id. If a tag's id is correctly decoded (i.e., no collision), the reader will ACK this 16-bit temporary id. The reader adjusts Q to better accommodate the remaining active tag population, and repeats the procedure until all tags are identified. We follow the Q adjustment algorithm described in the standard [14], which initially sets $Q = 4$. It increases Q to $Q + C$ when a collision is detected, and reduces Q to $Q - C$ when no tag replies. We use $C = 0.3$ as recommended by the standard.
- **FSA Augmented with Estimated K:** We feed $\widehat{K}$, the estimate of K derived from Stage 1 of Buzz's identification protocol to FSA. Once FSA knows $\widehat{K}$, it sets $Q = log_2\widehat{K}$, i.e., allocating $\widehat{K}$ slots, instead of $Q = 4$ as the initial value. The maximum throughput for FSA is known to be $\frac{1}{e} = 36.8\%$, and is achieved when the number of allocated slots is equal to the number of nodes [8, 16]. Hence, setting $Q = log_2\widehat{K}$ improves the efficiency of FSA. Further, knowing $\widehat{K}$ can help FSA work with a smaller temporary id space as in Buzz. Specifically, we let each tag in FSA transmit a shorter random temporary id in the slot it picks instead of the RN16. This reduces both the uplink and downlink transmission time in FSA.

We run the experiment for $K = 4$, 8, 12 and 16 Moo tags, and repeat for ten locations each. Fig. 14 shows the total amount of time spent on identifying the tags, including the overhead for ACKing the tags. While in Buzz, the reader only sends a single signal to tell all tags to stop, in the compared schemes, each tag needs to be ACKed individually.

For 16 tags, using Buzz's compressive sensing scheme achieves a 5.5× reduction in identification time over original FSA, and is 4.5× more efficient than FSA with estimated K. Also, as we can see, using the estimate of K from Stage 1 of Buzz reduces the identification time in FSA by 20%-40%. This is mainly because the size of the temporary id space is reduced to a function of K, instead of 2^{16}. In conclusion, by compressing the sparse identity space and reducing the reader feedback overhead, Buzz reaches the goal of significantly speeding up the node identification phase in backscatter systems. Combined with the 2× throughput gain in data transmission, Buzz reduces the overall communication time by 3.5×.

11. RELATED WORK

Various protocols have been proposed to improve the performance of backscatter communication [31]. Most of them are based on TDMA, such as Framed Slotted Aloha adopted by the EPC Gen-2 RFID protocol [14] and the binary search tree algorithm [31]. Researchers have also studied the use of CDMA in this scenario [37]. FDMA and SDMA based schemes are proposed in [36, 49]. The common problems with these anti-collision protocols are twofold. First, since collisions (over time, frequency, code or space) can never be efficiently eliminated, these systems still end up wasting resources over collisions. Second, they divide the medium evenly among all backscatter nodes which typically have diverse channels.

In the context of ultra-low power systems (e.g., passive RFIDs), [43] is the only piece of work similar to ours in the sense that it also aims to decode collisions. However, it does not reduce identification overhead, or address the rate adaptation problem, but instead focuses on decoding repeated collisions in a low frequency proximity card environment. Further, the heavy machine learning decoders employed in [43] are not practical in high throughput systems.

There has recently been a lot of work on decoding collisions in WiFi networks to increase throughput [26, 21]. However, applying these techniques to backscatter networks is challenging. Successive interference cancellation requires exponential differences in the power levels of colliding nodes [26]. ZigZag decoding requires an offset between colliding messages [21], which is inefficient given the short messages in backscatter systems.

In the area of compressive sensing, the closest to our work is an algorithm in [40] which eliminates chunks of the space to improve running time. However, it uses complex deterministic codes which are not applicable to low power backscatter networks. [17] provides a theoretical analysis of using compressive sensing for sparse detection in on-off random access channels. It requires nodes to transmit arbitrary values chosen from a Gaussian distribution, which is infeasible since backscatter nodes can only transmit binary values.

Belief propagation in a sparse scenario is best-known for its use in LDPC codes [20]. Our belief propagation algorithm is similar to a bit flipping algorithm introduced in [33]. However, the algorithmic novelty of Buzz lies in distributedly coding the bits of mutiple transmitters, on the air. Accordingly, Buzz's bit flipping algorithm is devised to effectively decode such a rateless code on a complex constellation graph representing multiple sources, unlike bit flipping decoding in the modulo-2 domain often employed by the coding theory community [33, 44].

Lastly, the rate adaptation problem in wireless networks has been extensively studied. Our design is inspired by recent advances in automatic rate adaptation using rateless codes, such as spinal and strider codes [39, 25], but differs in that we adapt the aggregate bit rate of the network through the design of a sparse distributed rateless code that is easy to decode using belief propagation.

12. CONCLUSION

For ultra-low power backscatter networks to reach the stage of widespread deployment, issues of reliability and efficiency must be addressed. This paper addresses these issues by modeling uplink transmissions in backscatter networks as if they were performed by a single virtual sender and treating collisions as a *sparse rateless* code across the nodes. We introduce a novel compressive sensing algorithm which significantly speeds up backscatter node identification and a belief propagation algorithm which enables distributed rate adaptation in data transfer. Evaluation of the new design shows a large improvement in both reliability and efficiency of backscatter communication.

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